Web Appendix

Heuristics and Biases in Data-Based Decision Making:

The Effects of Experience, Training, and Graphical Data Displays

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OVERVIEW

This Web Appendix provides the following supplementary materials for Hutchinson, Alba, and Eisenstein (2009): (1) an extended discussion of optimal and heuristic-based allocation policies, (2) the stimulus data used in all experiments, (3) a description of experiment A.1, which replicates the basic effects reported in the paper using stimuli that created global trend and local contrast variables more naturalistically rather than by sorting data from a factorial design, (4) experiment A.2, which tested the ability of explicit training to debias decision makers, and (5) an analysis of allocations to the control variable in experiment 2 that empirically separates trend-based and exemplar-based heuristics.

EXTENDED DISCUSSION OF OPTIMAL AND HEURISTIC-BASED ALLOCATION POLICIES

The schematic designs and linear transformations used in our experiments were chosen such that different heuristics for assessing covariation would favor different resource variables. In this appendix, the stimuli and their relationship to both optimal and heuristic-based allocation processes are described in greater detail than in the main text.

Although our stimuli were designed primarily to distinguish among optimal and various types of heuristic-based allocation processes, they are not unnatural. Many types of information interfaces allow users to sort by different variables, and other researchers have noted that such sorting is likely to influence decision making (e.g., Diehl, Kornish, and Lynch 2003; Feinberg and Huber 1996; Hutchinson and Alba 1997). Also, the diagnostic properties of comparing global trend and local contrast variables are not limited to those created by sorting. Any smooth pattern across adjacent observations creates a global trend (e.g., a quadratic pattern or a random pattern that is smoothed by positively correlated error between adjacent observations). Similarly, local contrast patterns can arise from deliberate experimentation or negatively correlated error between adjacent observations, among other causes. Sorting, however, simultaneously creates both patterns.

Optimal Allocations

In this section we more fully discuss what types of allocations can reasonably be interpreted as optimal or biased. As discussed earlier, the outcome variable in our stimulus data was generated as a linear function of the three resource variables plus a small amount of error. Thus, if the data were statistically analyzed, the analyst would find that a linear model predicts sales well and that there is no evidence of quadratic components for any of the resource variables. Assuming (1) that this linearity holds for the entire range of possible allocations (not just the observed range) and (2) that the parameters are stationary over time, then the *strictly optimal* allocation policy is straightforward: *allocate the entire budget to the resource variable with the largest regression coefficient* (see the first row of Table 1). This policy is optimal because the regression coefficient is the best estimate of the marginal return on expenditures.

There are a number of good arguments against the extreme allocations of the strictly optimal policy, however. First, even if both linearity and stationarity hold, if the decision maker had informative priors, say that the variables were equally effective, then the Bayesian estimates of the coefficients would be less extreme (e.g., a precision-weighted average of the prior and sample-based coefficients; see Gelman et al. 1995). Second, violations of the linearity and stationarity assumptions frequently militate in favor of more balanced policies. For example, when the response function is concave in all its arguments, the return on allocations to the resource variable with the largest regression coefficient will decrease as the spending level increases and, at some point, will fall below the return for the variable with the second-highest coefficient. Thus, a reasonable manager might recommend that most, but not all, of the budget be allocated to the resource variable with the highest regression coefficient, with the next highest portion going to variable with the next highest coefficient, and so on (e.g., Mantrala, Sinha, and Zoltners 1992). We refer to this type of policy as *robustly optimal*. Generally speaking, all extreme allocation policies are suspect, and extreme policies other than the strictly optimal policy are very far from optimal.

The second row of allocations in Table 1 shows a robustly optimal policy in which allocations are proportional to the regression coefficients, and it reveals two key properties of our data designs. First, the global trend and local contrast variables should always receive greater allocations than the control variable. Second, the best policies should favor the global trend variable for data designs 1 and 4 and favor the local contrast variable for designs 2 and 3. Of course, it is unlikely that people can compute regression coefficients in their heads. As noted in the text, however, in many situations, people can assess the difference between high and low correlations.

Heuristic-Based Allocations

In this section, we describe each type of heuristic and provide simplified examples of how they assess correlation. Figure A.1 illustrates each heuristic for the 16 observation data set used in data designs 1and 2a.

Figure A.1
SOME EXAMPLES OF BUDGET ALLOCATION HEURISTICS

Stimulus Data

	Outcome	Control	Global Trend	Local Contrast
	$56,535	$875	$806	$1,000
	$41,692	$750	$806	$250
	$64,594	$1,275	$806	$1,375
	$49,826	$1,425	$806	$625
	$71,078	$300	$1,063	$1,375
	$63,844	$525	$1,063	$1,000
	$56,836	$975	$1,063	$625
	$49,461	$1,050	$1,063	$250
	$58,235	$375	$1,319	$250
	$63,919	$600	$1,319	$625
	$71,678	$900	$1,319	$1,000
	$79,568	$1,350	$1,319	$1,375
	$71,228	$450	$1,575	$625
	$86,522	$825	$1,575	$1,375
	$64,444	$1,125	$1,575	$250
	$79,438	$1,200	$1,575	$1,000
Correlations with Outcome Variable		.03	.70	.71

Difference-Based Heuristic (Adjacent Differences)

	Outcome	Control	Global Trend	Local Contrast
	($14,843)	$75	$0	($750)
	$22,902	$525	$0	$1,125
	($14,768)	$150	$0	($750)
	$21,252	($1,125)	$256	$750
	($7,234)	$225	$0	($375)
	($7,009)	$450	$0	($375)
	($7,384)	$75	$0	($375)
	$8,784	($675)	$256	$0
	$7,684	$225	$0	$375
	$7,759	$300	$0	$375
	$7,909	$450	$0	$375
	($8,359)	($900)	$256	($750)
	$15,293	$375	$0	$750
	($22,077)	$300	$0	($1,125)
	$14,993	$75	$0	$750
Correlations with Outcome Variable		-.10	.18	.98
Predicted Allocations		*19%*	*25%*	*56%*

Trend-Based Heuristic (2-Period Moving Average)

	Outcome	Control	Global Trend	Local Contrast
	$49,113	$713	$806	$625
	$53,143	$1,013	$806	$813
	$57,210	$1,350	$806	$1,000
	$60,452	$863	$934	$1,000
	$67,461	$413	$1,063	$1,188
	$60,340	$750	$1,063	$813
	$53,143	$1,013	$1,063	$438
	$52,843	$713	$1,191	$250
	$60,077	$488	$1,319	$438
	$67,799	$750	$1,319	$813
	$75,633	$1,125	$1,319	$1,188
	$75,408	$900	$1,447	$1,000
	$78,875	$638	$1,575	$1,000
	$75,483	$975	$1,575	$813
	$71,941	$1,163	$1,575	$625
Correlations with Outcome Variable		.03	.83	.56
Predicted Allocations		*20%*	*45%*	*35%*

Exemplar-Based Heuristic (Best Exemplars)

Average of Best 3 Outcomes	$1,125	$1,490	$1,250
Predicted Allocations	*29%*	*39%*	*32%*

There are a number of plausible ways to generate predictions from heuristic-based transformations of the stimulus data. For difference-based and trend based heuristics, predicted allocations, a_{X_i}, were computed from correlations, $r_{X_i,Y}$, of resource variables, X_i, with the outcome variable, Y, after heuristic-based transformations of the stimulus data using a standard multinomial logit model, $a_{X_i} = \exp(r_{X_i,Y}) / [\exp(r_{G,Y}) + \exp(r_{L,Y})]$, where a_{X_i} is the allocation for variable i = G, or L. For the best-exemplars heuristic, predicted allocations were the average of the observed allocations for the three observations with the highest values for the outcome variable. We are primarily interested in the ordering of allocations, but it is useful to have some way to assess the magnitudes as well. The heuristic-based transformations are described below.

Difference-based heuristics. Difference-based heuristics are those that examine local changes in allocations for each resource variable and compare them to associated changes in the outcome variable. The version of this heuristic observed most frequently by Hutchinson and Alba (1997) was the *adjacent differences* heuristic (especially for time series data). To illustrate this heuristic consider the following data.

Global Trend Variable:	1	1	1	2	2	2	3	3	3
Local Contrast Variable:	0	1	2	0	1	2	0	1	2
Outcome Variable:	1	2	3	2	3	4	3	4	5

In this example, the global trend and local contrast variables each have three levels and are uncorrelated with each other. The outcome variable is the sum of the two resource variables, so the simple correlation of each with the outcome variable is .71. If people focus on adjacent differences, they will observe the following differences.

Global Trend Variable:	-	0	0	1	0	0	1	0	0
Local Contrast Variable:	-	1	1	-2	1	1	-2	1	1
Outcome Variable:	-	1	1	-1	1	1	-1	1	1

The outcome variable differences are perfectly correlated with the local contrast variable differences and perfectly negatively correlated with the global trend variable differences. Thus, the adjacent differences heuristic strongly favors the local contrast variable over the global trend variable. The stimuli used in our experiments were similar to this example. The global trend and local contrast variables each had four levels, were uncorrelated with each other, and were linearly combined to form the outcome variable (see Figure 2). The correlation between adjacent differences was .98 for the local contrast and outcome variables and .18 for the global trend and outcome variables for data design 1, 2, and 4 and .96 and -.03, respectively, for data design 3. Thus, the adjacent differences heuristic always favored the local contrast variable.

Trend-based heuristics. Rather than examining local changes, people might attempt to “smooth” the data and apprehend a general trend (e.g., increasing, decreasing, U-shaped, etc.). In all four data designs, both the outcome variable and the global trend variable exhibit a generally increasing trend. One index that captures trend is the correlation between variables that have been smoothed by a moving average. Returning to the earlier example, smoothing by averaging adjacent observations leads to the following.

Global Trend Variable:	-	1	1	1.5	2	2	2.5	3	3
Local Contrast Variable:	-	.5	1.5	1	.5	1.5	1	.5	1.5
Outcome Variable:	-	1.5	2.5	2.5	2.5	3.5	3.5	3.5	4.5

Notice how smoothing made the outcome variable monotonically increasing across observations, like the global trend variable. Correlations with the outcome variable favor the global trend variable (.87 vs. .50). Similarly, trend-based heuristics favor the global trend variable in all 4 designs used in our experiments (se Table 1).

Exemplar-based heuristics. Both difference-based and trend-based heuristics are clearly correlational in nature. Hutchinson and Alba (1997) found that a rather different—but naturally appealing—heuristic, the *best-exemplars* heuristic, was also commonly used (especially for cross-sectional data). The best-exemplars heuristic computes the average allocations for the observations with the highest values on the outcome variable and uses these averages as the basis for future allocations.

Returning to our example, the best-exemplars heuristic, like the trend-based heuristic, favors the global trend variable. The reason is different, however. The best exemplars heuristic favors the global trend variable simply because it has higher values on average (2 vs. 1). This is a major problem with all exemplar-based heuristics.

										Average
Global Trend Variable:	-	-	-	-	-	2	-	3	3	2.67
Local Contrast Variable:	-	-	-	-	-	2	-	1	2	1.67
Outcome Variable:	-	-	-	-	-	4	-	4	5	

For our stimuli, exemplar-based heuristics favor the global trend variable in experiments 1 and 2, but favors the control variable in experiment 3. Thus, experiment 3 allows us to distinguish between trend-based and exemplar based heuristics.

STIMULULI FOR ALL EXPERIMENTS

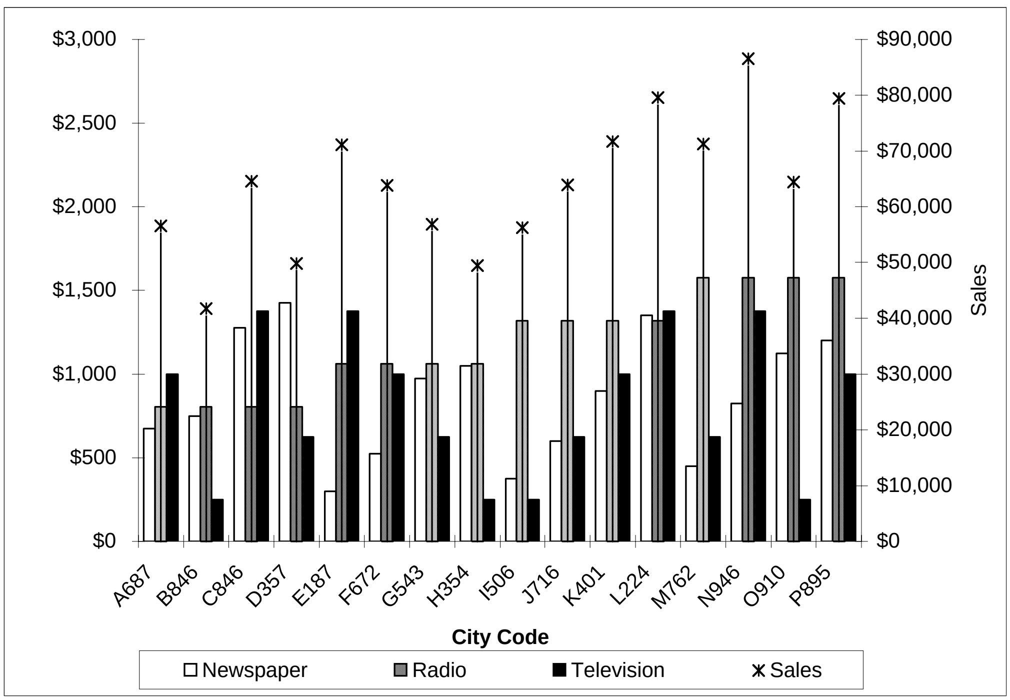
Stimuli for Experiment 1

Experiment 1 had 12 experimental conditions: graphical format (bars, lines, table), temporal frame (cross-sectional, time series), and prior beliefs (favors global trend, favors local contrast). Only the “favors local contrast” version of trend/shape are included; “favor global trend” can be created by reversing the labels.

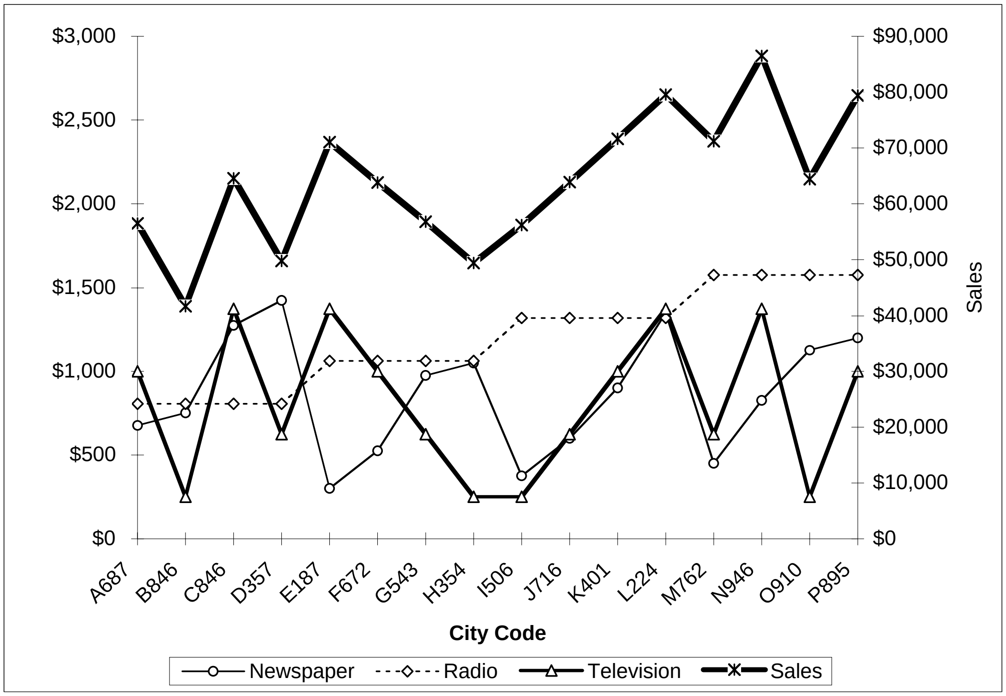
Table/CS/favors local contrast

City Code	Sales	Newspaper	Radio	Television
A687	$56,535	$675	$806	$1,000
B846	$41,692	$750	$806	$250
C846	$64,594	$1,275	$806	$1,375
D357	$49,826	$1,425	$806	$625
E187	$71,078	$300	$1,063	$1,375
F672	$63,844	$525	$1,063	$1,000
G543	$56,835	$975	$1,063	$625
H354	$49,451	$1,050	$1,063	$250
I506	$56,235	$375	$1,319	$250
J716	$63,919	$600	$1,319	$625
K401	$71,678	$900	$1,319	$1,000
L224	$79,588	$1,350	$1,319	$1,375
M762	$71,228	$450	$1,575	$625
N946	$86,522	$825	$1,575	$1,375
O910	$64,444	$1,125	$1,575	$250
P895	$79,438	$1,200	$1,575	$1,000

Bars/CS/favors local contrast



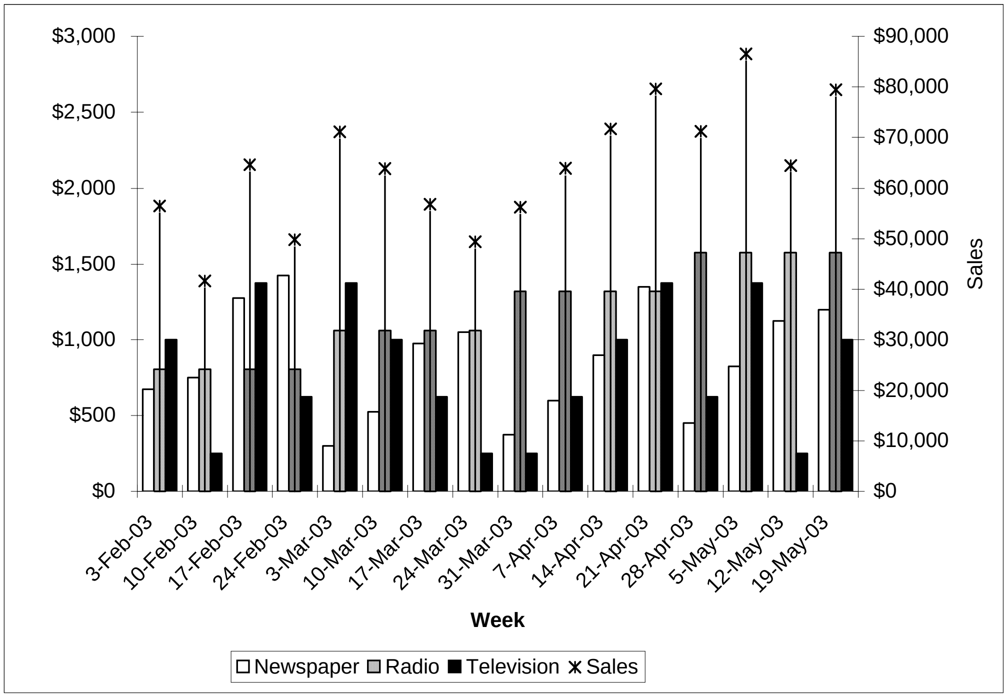
Lines/CS/favors local contrast



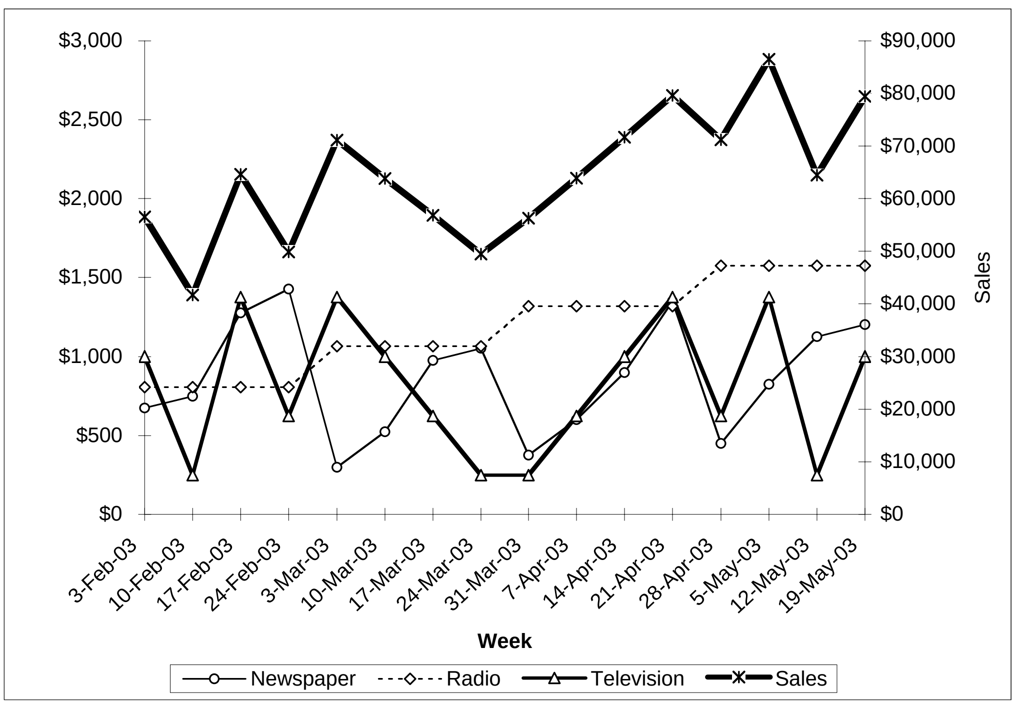
Table/TS/favors local contrast

Week	Sales	Newspaper	Radio	Television
3-Feb-03	$56,535	$675	$806	$1,000
10-Feb-03	$41,692	$750	$806	$250
17-Feb-03	$64,594	$1,275	$806	$1,375
24-Feb-03	$49,826	$1,425	$806	$625
3-Mar-03	$71,078	$300	$1,063	$1,375
10-Mar-03	$63,844	$525	$1,063	$1,000
17-Mar-03	$56,835	$975	$1,063	$625
24-Mar-03	$49,451	$1,050	$1,063	$250
31-Mar-03	$56,235	$375	$1,319	$250
7-Apr-03	$63,919	$600	$1,319	$625
14-Apr-03	$71,678	$900	$1,319	$1,000
21-Apr-03	$79,588	$1,350	$1,319	$1,375
28-Apr-03	$71,228	$450	$1,575	$625
5-May-03	$86,522	$825	$1,575	$1,375
12-May-03	$64,444	$1,125	$1,575	$250
19-May-03	$79,438	$1,200	$1,575	$1,000

Bars/TS/favors local contrast



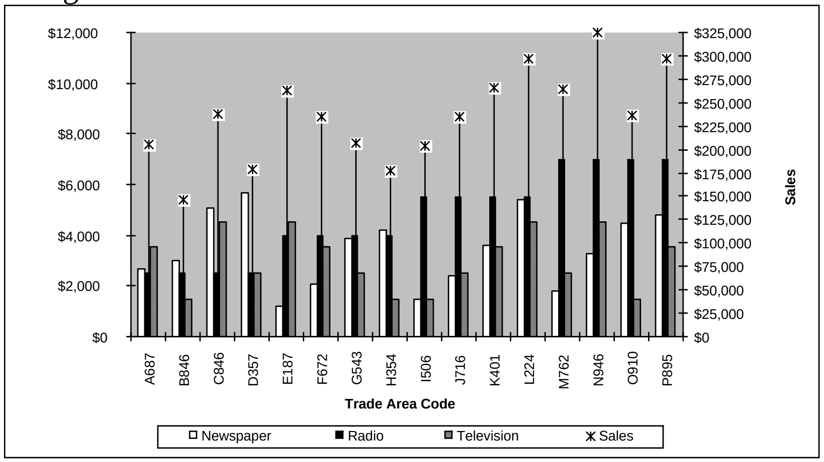
Lines/TS/favors local contrast



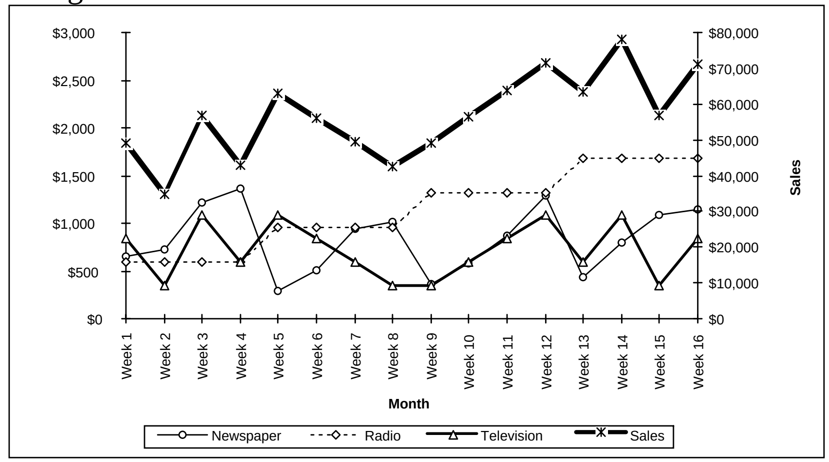
Stimuli for Experiment 2

Experiment 2 used a 2 x 2 x 2 x 2 between-subjects factorial design. The factors were prior beliefs (favors global trend, favors local contrast), temporal frame (cross-sectional, time series), graphical format (chart, table), and data design (2a, 2b; see Table 1). Only the “favors local contrast” version of trend/shape are included; “favor global trend” can be created by reversing the labels. The cross-sectional chart was a bar chart, and the time series chart was a line chart.

Design 2a/Bars/CS/favors local contrast



Design 2a/Lines/TS/favors local contrast



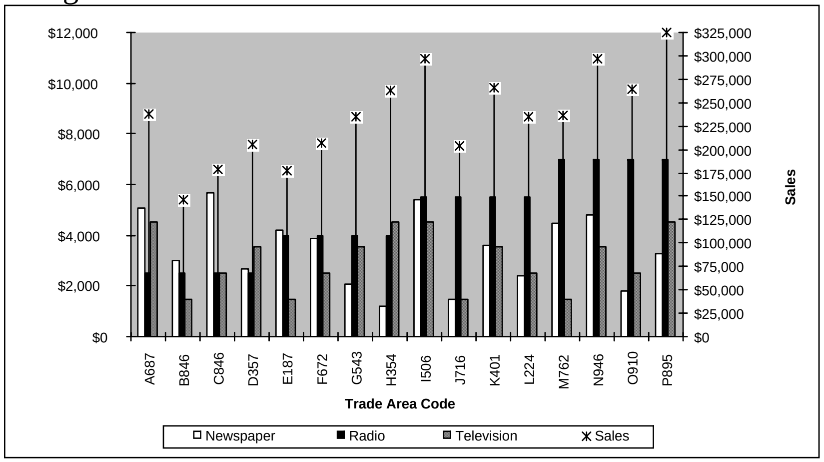
Design 2a/Table/CS/favors local contrast

Trade Area Code	Sales	Newspaper	Radio	Television
A687	$205,037	$2,700	$2,500	$3,525
B846	$145,663	$3,000	$2,500	$1,475
C846	$237,273	$5,100	$2,500	$4,550
D357	$178,200	$5,700	$2,500	$2,500
E187	$263,210	$1,200	$4,000	$4,550
F672	$234,273	$2,100	$4,000	$3,525
G543	$206,237	$3,900	$4,000	$2,500
H354	$176,700	$4,200	$4,000	$1,475
I506	$203,837	$1,500	$5,500	$1,475
J716	$234,573	$2,400	$5,500	$2,500
K401	$265,610	$3,600	$5,500	$3,525
L224	$297,247	$5,400	$5,500	$4,550
M762	$263,810	$1,800	$7,000	$2,500
N946	$324,983	$3,300	$7,000	$4,550
O910	$236,673	$4,500	$7,000	$1,475
P895	$296,647	$4,800	$7,000	$3,525

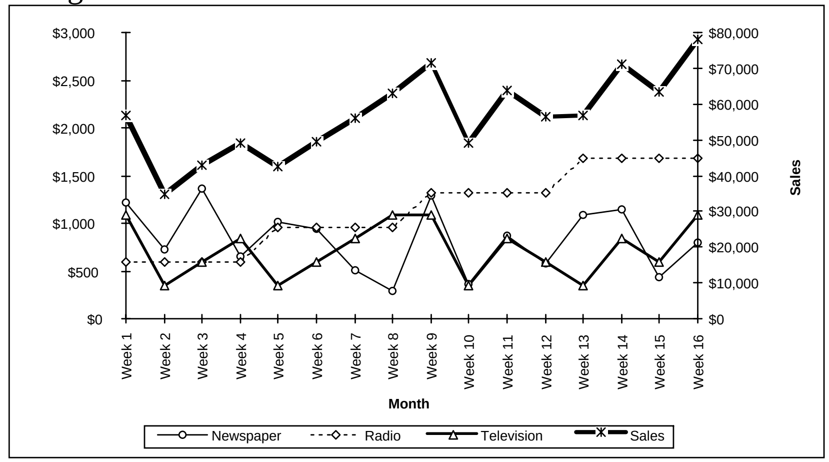
Design 2a/Table/TS/favors local contrast

	Sales	Newspaper	Radio	Television
Week 1	$51,259	$675	$625	$881
Week 2	$36,416	$750	$625	$369
Week 3	$59,318	$1,275	$625	$1,138
Week 4	$44,550	$1,425	$625	$625
Week 5	$65,802	$300	$1,000	$1,138
Week 6	$58,568	$525	$1,000	$881
Week 7	$51,559	$975	$1,000	$625
Week 8	$44,175	$1,050	$1,000	$369
Week 9	$50,959	$375	$1,375	$369
Week 10	$58,643	$600	$1,375	$625
Week 11	$66,402	$900	$1,375	$881
Week 12	$74,312	$1,350	$1,375	$1,138
Week 13	$65,952	$450	$1,750	$625
Week 14	$81,246	$825	$1,750	$1,138
Week 15	$59,168	$1,125	$1,750	$369
Week 16	$74,162	$1,200	$1,750	$881

Design 2b/Bars/CS/favors local contrast



Design 2b/Lines/TS/favors local contrast



Design 2b/Table/CS/favors local contrast

Trade Area Code	Sales	Newspaper	Radio	Television
A687	$237,273	$5,100	$2,500	$4,550
B846	$145,663	$3,000	$2,500	$1,475
C846	$178,200	$5,700	$2,500	$2,500
D357	$205,037	$2,700	$2,500	$3,525
E187	$176,700	$4,200	$4,000	$1,475
F672	$206,237	$3,900	$4,000	$2,500
G543	$234,273	$2,100	$4,000	$3,525
H354	$263,210	$1,200	$4,000	$4,550
I506	$297,247	$5,400	$5,500	$4,550
J716	$203,837	$1,500	$5,500	$1,475
K401	$265,610	$3,600	$5,500	$3,525
L224	$234,573	$2,400	$5,500	$2,500
M762	$236,673	$4,500	$7,000	$1,475
N946	$296,647	$4,800	$7,000	$3,525
O910	$263,810	$1,800	$7,000	$2,500
P895	$324,983	$3,300	$7,000	$4,550

Design 2b/Table/TS/favors local contrast

	Sales	Newspaper	Radio	Television
Week 1	$59,318	$1,275	$625	$1,138
Week 2	$36,416	$750	$625	$369
Week 3	$44,550	$1,425	$625	$625
Week 4	$51,259	$675	$625	$881
Week 5	$44,175	$1,050	$1,000	$369
Week 6	$51,559	$975	$1,000	$625
Week 7	$58,568	$525	$1,000	$881
Week 8	$65,802	$300	$1,000	$1,138
Week 9	$74,312	$1,350	$1,375	$1,138
Week 10	$50,959	$375	$1,375	$369
Week 11	$66,402	$900	$1,375	$881
Week 12	$58,643	$600	$1,375	$625
Week 13	$59,168	$1,125	$1,750	$369
Week 14	$74,162	$1,200	$1,750	$881
Week 15	$65,952	$450	$1,750	$625
Week 16	$81,246	$825	$1,750	$1,138

Stimuli for Experiment 3

Experiment A.1 used a 2 x 2 x 2 between-subjects factorial design. The factors were prior beliefs (favors global trend, favors local contrast), temporal frame (cross-sectional, time series), and graphical format (chart, table). Only the “favors local contrast” version of trend/shape are included; “favor global trend” can be created by reversing the labels. The cross-sectional chart was a bar chart, and the time series chart was a line chart. Data design 3 was used for this experiment.

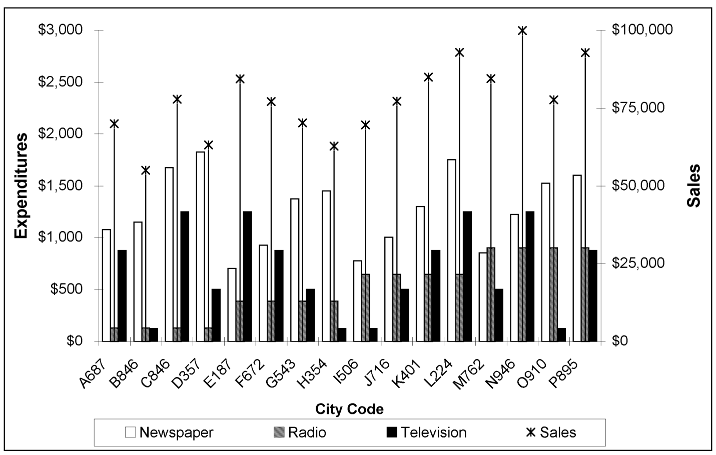
Cross-Sectional, Table, favors local contrast

City Code	Sales	Newspaper	Radio	Television
A687	$69,800	$1,075	$131	$875
B846	$54,957	$1,150	$131	$125
C846	$77,859	$1,675	$131	$1,250
D357	$63,091	$1,825	$131	$500
E187	$84,344	$700	$388	$1,250
F672	$77,109	$925	$388	$875
G543	$70,100	$1,375	$388	$500
H354	$62,716	$1,450	$388	$125
I506	$69,500	$775	$644	$125
J716	$77,184	$1,000	$644	$500
K401	$84,944	$1,300	$644	$875
L224	$92,853	$1,750	$644	$1,250
M762	$84,494	$850	$900	$500
N946	$99,787	$1,225	$900	$1,250
O910	$77,709	$1,525	$900	$125
P895	$92,703	$1,600	$900	$875

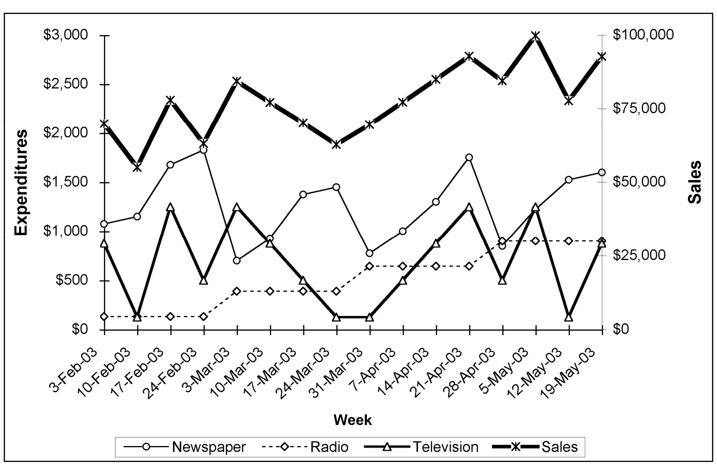
Time-Series, Table, favors local contrast

Week	Sales	Newspaper	Radio	Television
3-Feb-03	$69,800	$1,075	$131	$875
10-Feb-03	$54,957	$1,150	$131	$125
17-Feb-03	$77,859	$1,675	$131	$1,250
24-Feb-03	$63,091	$1,825	$131	$500
3-Mar-03	$84,344	$700	$388	$1,250
10-Mar-03	$77,109	$925	$388	$875
17-Mar-03	$70,100	$1,375	$388	$500
24-Mar-03	$62,716	$1,450	$388	$125
31-Mar-03	$69,500	$775	$644	$125
7-Apr-03	$77,184	$1,000	$644	$500
14-Apr-03	$84,944	$1,300	$644	$875
21-Apr-03	$92,853	$1,750	$644	$1,250
28-Apr-03	$84,494	$850	$900	$500
5-May-03	$99,787	$1,225	$900	$1,250
12-May-03	$77,709	$1,525	$900	$125
19-May-03	$92,703	$1,600	$900	$875

Cross-Sectional, Chart, favors local contrast



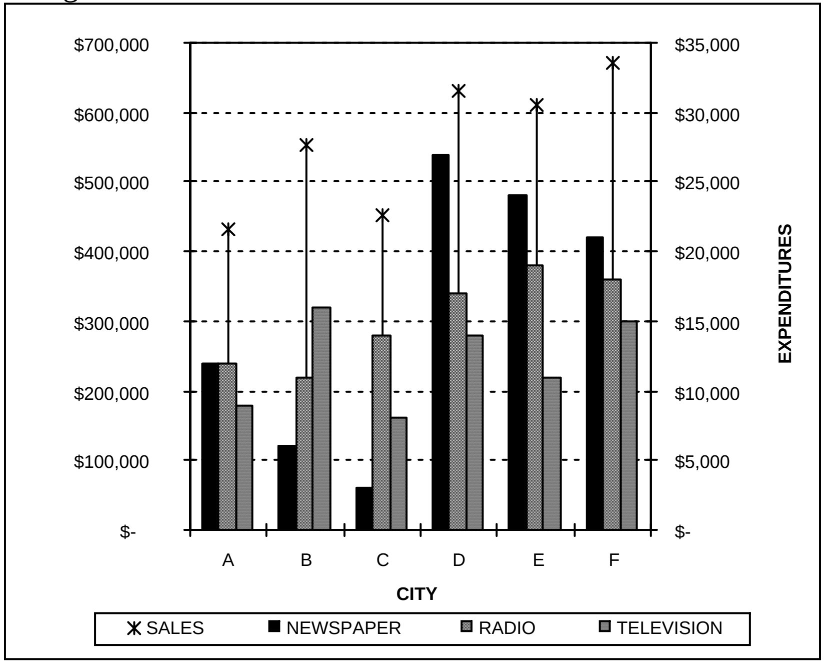
Time-Series, Chart, favors local contrast



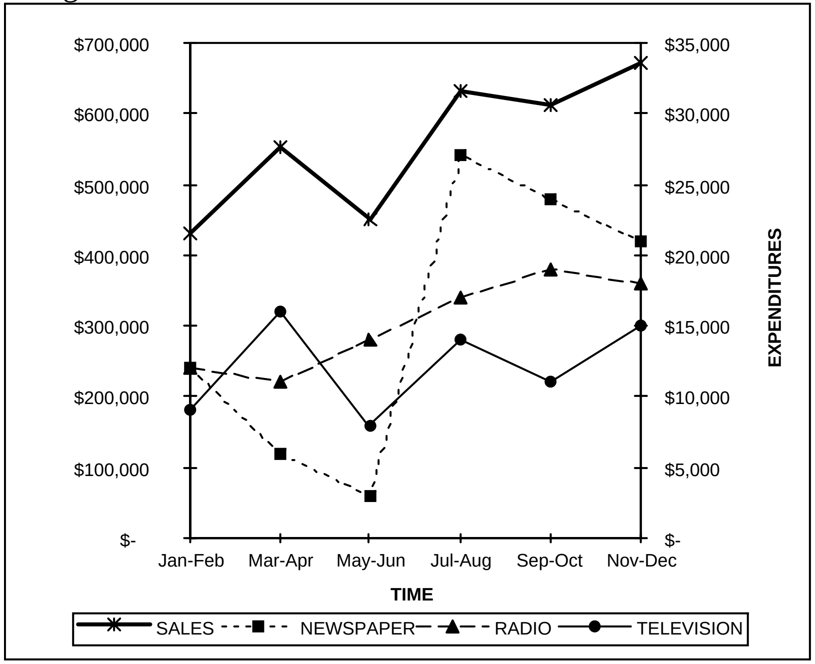
Stimuli for Experiment A.1

Experiment A.1 used a 2 x 2 x 2 between-subjects factorial design. The factors were prior beliefs (favors global trend, favors local contrast), temporal frame (cross-sectional, time series), and graphical format (chart, table). Only the “favors local contrast” version of trend/shape are included; “favor global trend” can be created by reversing the labels. The cross-sectional chart was a bar chart, and the time series chart was a line chart. Data design 4 was used for this experiment because, like designs 1 - 3, the control variable is uncorrelated with outcomes. A second experiment using data design 5 was run at the same time. For data design 5, the "control" variable contributed to outcomes and its regression coefficient was approximately half the size of the coefficients for the global trend and local contrast variables.

Design 4/Bars/CS/favors local contrast



Design 4/Lines/TS/favors local contrast



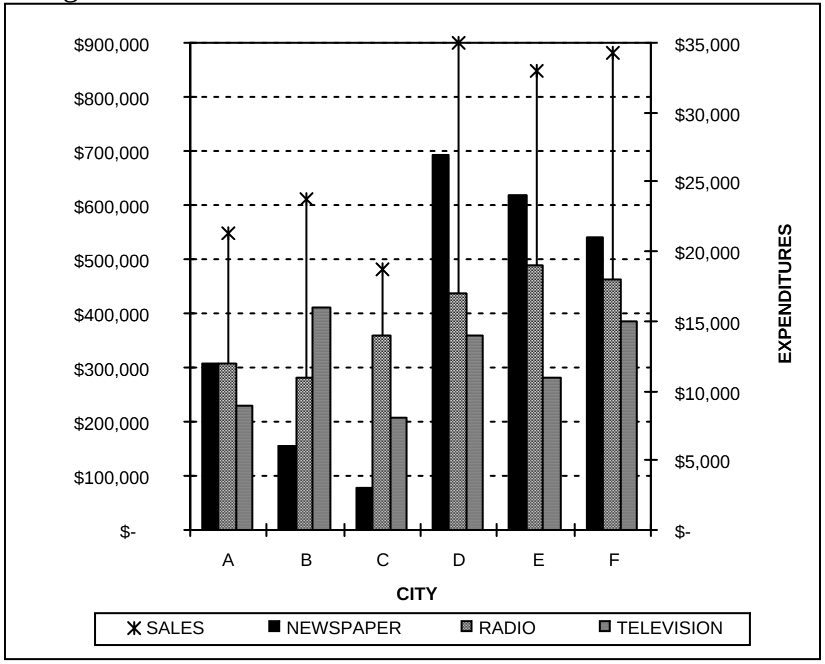
Design 4/Table/CS/favors local contrast

CITY	SALES	NEWSPAPER	RADIO	TELEVISION
A	$ 432,000	$ 12,000	$ 12,000	$ 9,000
B	$ 552,000	$ 6,000	$ 11,000	$ 16,000
C	$ 452,000	$ 3,000	$ 14,000	$ 8,000
D	$ 632,000	$ 27,000	$ 17,000	$ 14,000
E	$ 612,000	$ 24,000	$ 19,000	$ 11,000
F	$ 672,000	$ 21,000	$ 18,000	$ 15,000

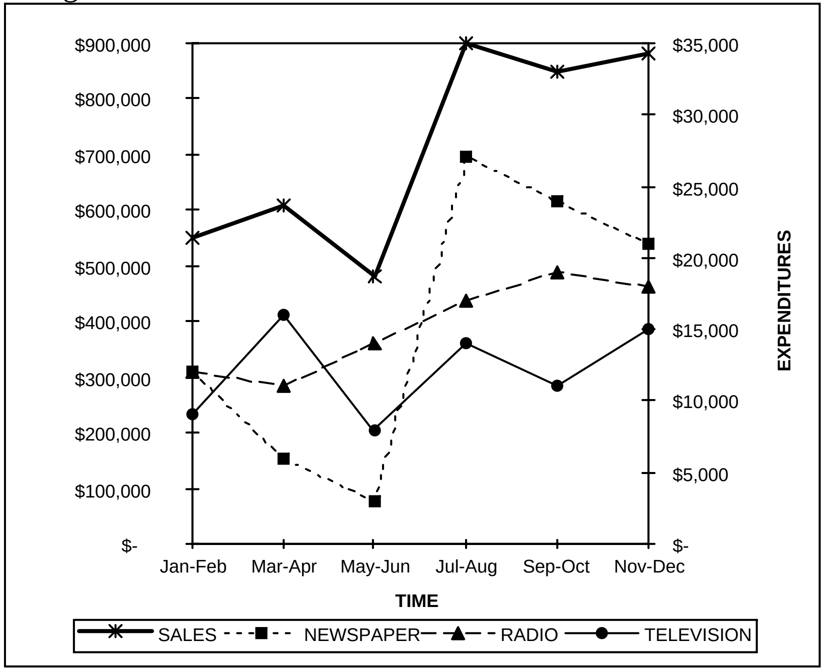
Design 4/Table/TS/favors local contrast

TIME PERIOD	SALES	NEWSPAPER	RADIO	TELEVISION
Jan-Feb	$ 432,000	$ 12,000	$ 12,000	$ 9,000
Mar-Apr	$ 552,000	$ 6,000	$ 11,000	$ 16,000
May-Jun	$ 452,000	$ 3,000	$ 14,000	$ 8,000
Jul-Aug	$ 632,000	$ 27,000	$ 17,000	$ 14,000
Sep-Oct	$ 612,000	$ 24,000	$ 19,000	$ 11,000
Nov-Dec	$ 672,000	$ 21,000	$ 18,000	$ 15,000

Design 5/Bars/CS/favors local contrast



Design 5/Lines/TS/favors local contrast



Design 5/Table/CS/favors local contrast

CITY	SALES	NEWSPAPER	RADIO	TELEVISION
A	$ 550,000	$ 12,000	$ 12,000	$ 9,000
B	$ 610,000	$ 6,000	$ 11,000	$ 16,000
C	$ 480,000	$ 3,000	$ 14,000	$ 8,000
D	$ 900,000	$ 27,000	$ 17,000	$ 14,000
E	$ 850,000	$ 24,000	$ 19,000	$ 11,000
F	$ 880,000	$ 21,000	$ 18,000	$ 15,000

Design 5/Table/TS/favors local contrast

TIME PERIOD	SALES	NEWSPAPER	RADIO	TELEVISION
Jan-Feb	$ 550,000	$ 12,000	$ 12,000	$ 9,000
Mar-Apr	$ 610,000	$ 6,000	$ 11,000	$ 16,000
May-Jun	$ 480,000	$ 3,000	$ 14,000	$ 8,000
Jul-Aug	$ 900,000	$ 27,000	$ 17,000	$ 14,000
Sep-Oct	$ 850,000	$ 24,000	$ 19,000	$ 11,000
Nov-Dec	$ 880,000	$ 21,000	$ 18,000	$ 15,000

EXPERIMENT A.1: GLOBAL TREND AND LOCAL CONTRAST WITHOUT SORTING

The goal of this experiment was to explore the generalizability of the results found in the text by using stimulus designs that differed in major ways from those used in experiments 1, 2, and 3. Therefore, the stimuli had 6 rather 16 observations, and the global trend variable was not monotonically increasing over observations (i.e., top to bottom for tables, and left to right for charts). Also, the global trend and local contrast variables were drawn from a pseudo-random design rather than a 4 x 4 factorial design. Finally, the correlational structure among variables was different. Data design 4 was used. As in the other experiments, the global trend and local contrast variables were equally correlated with the outcome variable (r = .74) and minimally correlated with each other (r = .11). Their regression coefficients were equal. The control variable was rather different, however. It was highly correlated with the outcome variable (r = .77) and with global trend (r = .82), but not with the local contrast variable (r = .33). Importantly, the partial correlation of the control with the outcome variable when the other two variables were included was zero (i.e., its regression coefficient was zero). Thus, from the perspective of optimal allocations this design is essentially the same as the others. However, many other aspects of this design are different.

Method

Participants. A total of 115 undergraduate volunteers who were taking an introductory marketing course at the University of Pennsylvania participated in experiment A.2.

Design. The experiment used a 2 x 2 x 2 between-subjects factorial design. Data design 5 was used (see earlier discussion). The factors were prior beliefs (favored the global trend variable vs. favored the local contrast variable), temporal frame (cross-sectional vs. time series), and graphical format (chart vs. table). To simplify the design but still create strong effects as in experiment 2, the cross-sectional chart was a bar chart and the time series chart was a line chart.

Instructions and stimuli. Other than the changes in schematic design and linear transformations described earlier, the instructions were the same as in experiments 1 and 2.

Results

The data were analyzed as in experiments 1 and 2.

Prior beliefs. The effects of prior beliefs were as expected. The mean allocation for the variable labeled "Television" was 37 and it was chosen as most effective by 35% of participants, whereas the mean allocation for the variable labeled "Radio" was 32 and it was chosen as most effective by 24% of participants. The effect of prior beliefs on allocation differences was statistically significant ($F(1, 107) = 4.8$, $p = .03$, $MSE = 609$). Similarly, the local contrast variable was chosen as most effective more often when labeled "Television" (60% vs. 38%, $\chi_1^2 = 5.3$, p = .02). There was no effect for the global trend variable, and this is true for all other effects (although they are frequently in the right direction). This pattern suggests that allocations to global trend were suppressed by its strong correlation with the control variable. The result makes intuitive sense, but is not predicted by any of the heuristics and suggests an interesting direction for future research.

Temporal frame and graphic format. Unlike the experiments with 16-observation stimuli, the results for these 6-observation stimuli showed no interaction of frame and format.

There were simple effects for each factor, however, replicating the basic results of the other experiments. Evidently, with fewer observations, people can execute heuristics (especially difference-based heuristics) for tables, which has the effect of eliminating the interaction without eliminating the general facilitation effect of charts. The main effect of frame was significant for allocation differences (i.e., global trend minus local contrast; $M_{cross\text{-}sectional}$ = -5 and $M_{time\ series}$ = -15, $F(1, 107) = 4.3$, $p = .04$, $MSE = 609$), and marginally significant for choice of the local contrast variable as most effective ($M_{cross\text{-}sectional}$ = .42 and $M_{time\ series}$ = .55, $\chi_1^2 = 1.9$, p = .17). The main effect of format was significant for allocation differences (M_{charts} = -15 and M_{tables} = -5, $F(1, 107) = 4.1$, $p = .05$, $MSE = 609$), and for choice of the local contrast variable as most effective (M_{charts} = .58 and M_{tables} = .40, $\chi_1^2 = 3.7$, p = .05). Recall that from a normative perspective, neither temporal frame nor graphic format should affect allocations. Thus, the presence of heuristic-based biases is strongly indicated.

EXPERIMENT A.2: DEBIASING

The experiments in the text (especially experiments 1 and 2) demonstrated that presenting data in line charts and as time series biases people to over-allocate to the local contrast variable, and that the magnitude of this bias is larger than the established biases of prior beliefs. Real world experience did not reduce the bias, and graphical display by line graphs, if anything, increased it. This result is similar to that of Boulding, Morgan, and Staelin (1997), who found that enriching and improving the information environment had minimal effects in reducing escalation-of-commitment biases (also see Kahn, Luce, and Nowlis, 2006 and Larrick 2004). Boulding et al. found that interventions that affected the rule used for decision making were more successful. Experiment A.2 examines the extent to which the biases revealed in Experiments 1 and 2 can be reduced by interventions designed to affect the heuristics used in our budget allocation task.

Arkes (1991; see also Larrick 2004) classified a large number of decision biases into three types based on the source of the bias and its resistance to debiasing. The first type, *strategy-based errors*, arises from deliberate tradeoffs between accuracy and cost. Raising the incentives for accuracy can alleviate such biases (e.g., by increasing the use of compensatory decision rules rather than non-compensatory rules). The second type, *association-based errors*, results from the associative nature of memory, which sometimes increases the salience of irrelevant information while lowering the salience of important information. Such biases are not affected by incentives but can be reduced by specific cues that make important information easier to retrieve from memory. For example, overconfidence, hindsight, and anchoring biases are reduced simply by instructing people to “consider the opposite” of their current belief (Larrick 1986). The third type, *perceptual error,* is highly resistant to debiasing, and people often find the “wrong” answer compelling even after the “right” answer has been explained to them (e.g., loss aversion, including framing effects, and status quo biases). Arkes notes that professional training can be an effective, albeit time-intensive, debiasing intervention. In experiment A.2, we use several debiasing interventions that combine monetary incentives, the consider-the-opposite technique, and training.

Method

Participants. A total of 225 undergraduate volunteers from an introductory marketing class at the University of Pennsylvania participated for partial course credit. Participants were also informed that the person who performed best would win $50. One participant was dropped for failure to respond completely.

Stimuli. The stimuli consisted of one cross-sectional stimulus (i.e., design 2b, cross-sectional/bar chart/favors global trend) and one time series stimulus (i.e., design 5, time series/line chart/favors local contrast). These stimuli were chosen because they were shown to generate large biases in allocation, with the first favoring the global trend variable and the second favoring the local contrast variable. To explore the generality of biases in data-based inference tasks we also created two variations of these charts, which were framed as finance problems rather than marketing problems.

Each stimulus was accompanied by a one-paragraph cover story that included instructions about the allocation task to be performed. Each cover story related either a marketing problem or a finance problem. The marketing problems were essentially the same as those used in experiments 1 and 2. The time series finance problem used the same numerical information and graphical display as the marketing problem but described the resource variables as investments in small-, mid-, and large-cap stocks, and the outcome variable as the Russell 2000 stock index. The task for this problem was to allocate funds among the three stocks so as to mimic, or track, the stock index. The cross-sectional finance problem described the resource variables as the percentage allocations of 16 mutual funds across the telecommunications, software/hardware, and entertainment sectors. The outcome variable was the percentage return for each fund. The task was to specify the allocations of assets for a new mutual fund that would maximize percentage return. Although different from the marketing problem in some respects, optimal allocations for the finance problems also depend on regression coefficients and are directionally consistent with robustly optimal allocations for the marketing problems.

Design and procedure. Participants were randomly assigned to one of 12 experimental conditions: training (control, explain, learn), design (favors global trend, favors local contrast), and domain (finance, marketing). The task was computer mediated. Participants first saw an introductory screen that contained general information about the experiment and forewarning of the “helpful hints” (i.e., the training conditions), quiz on the helpful hints, two short business problems, and short questionnaire that were to follow. After clicking a hyperlink at the bottom of the page, participants were exposed to one of the three training conditions.

The explain form of training defined the three heuristics, warned against best exemplars, and recommended the combined use of adjacent-differences and trend-based heuristics. This intervention is a form of the consider-the-opposite approach, given that adjacent-differences and trend-based heuristics rely upon different aspects of the data and favor different resource variables for our stimuli. The learn form of training was an extension of the explain form that provided participants with specific examples of different levels of correlation in addition to verbal instructions about the heuristics. The control form simply exhorted participants to examine all the data and think carefully. Allocation task instruction were similar to those of experiments 1 and 2. (Details of the stimuli, training procedures, and instructions are available from the authors.) Finally, an exit questionnaire gathered demographic information and self-reports of the number of courses taken in statistics, marketing, and finance.

Results

Because the effects of the difference between explain and learn conditions were small, the training factor was collapsed to two levels (i.e., control vs. debias, which combined the explain and learn conditions). The full analyses (i.e., using all 3 levels of training) yielded substantively identical results as the simplified analysis.

Measures of expertise included number of statistics courses, number of economics courses, number of marketing courses, number of finance courses, total business courses, being a business major, and post-training quiz score. None of these measures was significantly correlated with accuracy as measured by absolute deviations, either across all conditions or when the levels of training and domain were analyzed separately. In fact, the only correlation that approached significance was for being a business student, which was associated with greater error ($r = .18$, $p = .06$). Except for a small correlation between difference scores and total business-related courses when the stimulus domain was marketing ($r = -.21$, $p = .04$), the expertise measures were also uncorrelated with difference scores. These null results support the conclusion that the observed bias is perceptual in nature and very difficult to ameliorate.

An ANOVA of allocation differences (i.e., global trend minus local contrast) revealed a strong main effect of design that was consistent with expectations ($M = 2$ for "all factors favor global trend" and $M = -24$ for "all factors favor local contrast"), $F(1, 216) = 38.8$, $p < .0001$, $MSE = 1026$. No other main effects or interactions reached statistical significance. Similarly, only a main effect of stimulus design was found for choice of global trend as most effective ($M = .71$ for "all factors favor global trend" and $M = .30$ for "all factors favor local contrast"), $\chi^2 = 33.6$, $p < .0001$. These results replicate experiments 1and 2. As before, this result is notably contrary to optimal allocation.

Discussion

The results of experiment A.2 testify to the robustness of the effects of graphical format, temporal frame, and prior beliefs found in experiments 1 and 2. These biases were not eliminated by explicit training about correlation, a consider-the-opposite countermeasure, monetary incentives, or pre-experimental expertise. Taken together, the results provide compelling evidence that the biases revealed by our paradigm were perceptually driven, as defined by Arkes (1991).

ANALYSIS OF ALLOCATIONS TO THE CONTROL VARIABLE

Table A.1 shows that difference-based heuristics predict *smaller* allocations to the control variable for data design 2a than for 2b, trend-based heuristics predict *larger* allocations for data design 2a than for 2b, and exemplar-based heuristics predict that they will be *equal*. As discussed earlier, both trend-based and exemplar-based heuristics favor the global trend variable over the local contrast variable for all data sets in experiments 1 and 2. Thus, comparing allocations to the control variable for data designs 2a and 2b provides a way of distinguishing between the two that supplements the results of experiment 3. It turns out that difference-based heuristics also make informative predictions about allocations to the control variable for data designs 4 and 5 (see Table A.1 and subsequent discussion). Trend-based and exemplar-based heuristics both predict that allocations to the control variable will be approximately equal for data designs 4 and 5; however, trend-based heuristics predict that these allocations will be approximately equal to the allocation to the global trend variable while exemplar-based heuristics predict that allocations to the control variable will be considerably larger.

To test these predictions, we separately analyzed allocations to the control variable for subjects who favored the global trend variable. For data from experiment 2, the allocations were nearly identical (M = 22 and 24 for data sets 2a and 2b, respectively), and the difference was not significant ($F(1, 210) = 1.1$, $p > .25$, $MSE = 96$). For data from experiment A.2 (both designs 4 and 5), allocations to the control variable were considerably larger than allocations to the global trend variable for those who chose either the control or the global trend variables as most effective ($M_{control}$ = 43 and $M_{global\ trend}$ = 32, $F(1, 107) = 22.5$, $p < .0001$, $MSE = 281$, based on repeated measures ANOVA). These results strongly suggest that exemplar-based heuristics were more prevalent than trend-based heuristics among subjects who did not choose the local contrast variable as most effective. Among subjects who favored the local contrast variable, allocations to the control variable were consistent with the prediction of the difference-based heuristic. Specifically, the correlations between difference-based heuristic transformations of the outcome and control variables are -.10, .57, .60, and .91, respectively, for data sets 2a, 2b, 4, and 5 (see Table A.1), and the observed allocations to the control variable were 16, 25, 25, and 35; the effect was significant when the data were pooled across experiments 2 and A.1 ($F(3, 179) = 11.9$, $p < .0001$, $MSE = 215$). Overall, these analyses suggest that difference-based and exemplar-based heuristics were relatively frequent, but trend-based heuristics were rare.

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Table A.1
SUMMARY OF STIMULUS DESIGNS FOR EXPERIMENTS 1 AND 2 SHOWING HOW ALLOCATION HEURISTICS DIFFER FROM OPTIMAL ALLOCATIONS BASED ON REGRESSION COEFFICIENTS

Design		4			5			2b			2a			1	
Experiment		A.1			A.2			2			2			1	
Number of Observations		6			6			16			16			16	
Resource Variable	C	GT	LC	C	GT	LC	C	GT	LC	C	GT	LC	C	GT	LC
Normative Indices:															
Regression Coefficient (β)	0	**20***	**20**	10	**20**	**20**	1	20	**29**	1	20	**29**	1	**29**	20
Simple Correlation (*r*)	.77	**.74**	**.74**	.94	**.83**	.57	.03	**.70**	**.71**	.03	**.70**	**.71**	.03	**.70**	**.71**
Difference-Based Heuristics:															
Adjacent Differences (*r*)**	.60	-.29	**.95**	.91	.16	**.71**	.57	-.03	**.96**	-.10	.18	**.98**	-.10	.18	**.98**
Adjacent Changes (*r*)	.41	-.67	**1.00**	.41	-.67	**1.00**	.38	.00	**.84**	-.13	.13	**.97**	-.13	.13	**.97**
Trend-Based Heuristics:															
Moving Average (2, *r*)**	.94	**.98**	.47	.99	**.97**	.41	-.46	**.85**	.58	.03	**.83**	.56	.03	**.83**	.56
Moving Average (4, *r*)	.98	**.99**	.60	.99	**.99**	.53	-.46	**.90**	.44	.18	**.87**	.49	.18	**.87**	.49
Exemplar-Based Heuristics:															
Best 3 Observations (%)**	.43	**.33**	.24	.43	**.33**	.24	.30	**.43**	.28	.30	**.43**	.28	.29	**.39**	.32
All Observations (%)	.36	**.35**	.29	.36	**.35**	.29	.31	**.42**	.27	.31	**.42**	.27	.30	**.42**	.28

KEY: C - control variable; GT - global trend variable; LC- local contrast variable; β - regression coefficient when the outcome variable is regressed onto the resource variables; *r* - simple Pearson correlation between resource and outcome variables; % - average allocation as a proportion of the sum of the three average allocations.

* Bold values indicate the variable with the largest allocation.

** Used to make predictions in the text (see Table 1).

Table A.2
SUMMARY OF STIMULUS DESIGNS SHOWING HOW HEURISTICS-BASED ALLOCATIONS DIFFER FROM OPTIMAL ALLOCATIONS TOGETHER WITH OBSERVED MEAN ALLOCATIONS AND PROPORTIONS OF PARTICIPANTS CHOOSING EACH RESOURCE VARIABLE AS MOST EFFECTIVE FOR EACH EXPERIMENT

Experiment		1			2			2			3	
Data Design		1			2a			2b			3	
Resource Variable	C	G	L	C	G	L	C	G	L	C	G	L
Allocations Predicted by Normative Indices												
Strictly Optimal	0	**100**	0	0	0	**100**	0	0	**100**	0	**100**	0
Robustly Optimal	2	**58**	40	2	40	**58**	2	40	**58**	2	**58**	40
Allocations Predicted by Heuristic-Based Indices												
Difference-Based	19	25	**56**	19	25	**56**	32	19	**49**	19	25	**56**
Trend-Based	22	**45**	33	22	**45**	33	13	**51**	36	22	**45**	33
Exemplar-Based	30	**40**	30	30	**43**	27	30	**43**	27	**48**	22	30
Observed Mean Allocations (Proportions of Participants Choosing Each Resource Variable as Most Effective)												
Grand Means	22	38	**40**	19	**43**	38	24	**40**	37	**37**	27	36
	(.05)	(**.48**)	(.37)	(.01)	(**.63**)	(.36)	(.06)	(**.54**)	(.36)	(**.43**)	(.14)	(.31)
Temporal frame												
Cross-Sectional	20	39	**41**	21	**46**	32	24	**46**	31	**39**	26	35
	(.01)	(**.52**)	(.34)	(.02)	(**.78**)	(.20)	(.04)	(**.74**)	(.17)	(**.48**)	(.12)	(.27)
Time-Series	24	37	**39**	18	40	**43**	23	35	**42**	34	28	**37**
	(.08)	(**.43**)	(.39)	(.00)	(.47)	(**.51**)	(.07)	(.34)	(**.54**)	(**.38**)	(.17)	(.34)
Graphic Format												
Tables	25	**40**	35	21	**44**	35	25	**40**	35	**37**	27	35
	(.05)	(**.54**)	(.27)	(.00)	(**.64**)	(.36)	(.09)	(**.53**)	(.34)	(**.37**)	(.17)	(.31)
Bars	20	**43**	37	21	**49**	30	24	**47**	30	**39**	25	36
	(.03)	(**.60**)	(.30)	(.04)	(**.85**	(.11)	(.00)	(**.81**)	(.10)	(**.54**)	(.08)	(.28)
Lines	20	30	**50**	15	35	**50**	21	34	**45**	33	29	**38**
	(.07)	(.30)	(**.54**)	(.00)	(.36)	(**.59**)	(.03)	(.30)	(**.57**)	(**.46**)	(.15)	(.33)
Prior Beliefs												
Favor Global	21	**40**	39	21	**47**	32	23	**43**	39	**38**	29	33
	(.02)	(**.54**)	(.33)	(.00)	(**.74**)	(.24)	(.04)	(**.58**)	(.35)	(**.45**)	(.16)	(.28)
Favor Local	22	36	**42**	17	39	**43**	24	**37**	34	36	25	**39**
	(.07)	(**.41**)	(.40)	(.02)	(**.54**)	(.44)	(.08)	(**.46**)	(.37)	(**.41**)	(.13)	(.33)

Notes: Resource variables are labeled as follows, "C" for control, "G" for global trend, and "L" for local contrast. Predicted allocations, a_{Xi}, were computed from correlations, $r_{Xi,Y}$, of resource variables, X_i, with the outcome variable, Y, after heuristic-based transformations of the stimulus data using a standard multinomial logit model, $a_{Xi} = \exp(r_{Xi,Y}) / [\exp(r_{C,Y}) + \exp(r_{G,Y}) + \exp(r_{L,Y})]$, where a_{Xi} is the allocation for variable i = C, G, or L (except best-exemplars heuristics use averages of observed allocations; see Appendix for details). For each participant, a variable was selected as most effective if it received the highest allocation (if two variables received the same highest value, neither was counted as having been selected). Bold values indicate the variable with the largest allocation. Temporal Frame and Graphic Format were orthogonally varied in Experiment 1; in Experiments 2 and 3 all bar charts were cross-sectional and all line charts were time series.