Morphing Banner Advertising

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April 2012

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This research was supported by the MIT Sloan School of Management, the Center for Digital Business at MIT (ebusiness.mit.edu), GM, WPP/Kantar, Google, CNET.com. We gratefully acknowledge the contributions of our industrial collaborators, research assistants, and faculty colleagues: Dorothee Bergin, Angela Chow, Tousanna Durgan, Shirley S. Fung, Will Hansen, Patricia Hawkins, Douglas Hwang, Tom Kelley, Jong-Moon Kim, Clarence Lee, Jimmy Li, Cordelia Link, Ladan Nafissi, Andy Norton, Jonathon Owen, George Pappachen, Chris Perciballi, Joyce Salisbury, Linda Tan, David Vanderveer, and Kevin Wang.

Morphing Banner Advertising

Abstract

Morphing enables a website to learn (actively and near optimally) which banner advertisements to serve to each cognitive-style segment in order to maximize outcome measures such as click-through, brand consideration, or purchase. Consumer segments are identified automatically from consumers' clickstream choices. Morphing works best on high-traffic websites with tens of thousands of visitors because large samples are necessary to reach steady state optimally.

This paper describes the first large-sample random-assignment field test of banner morphing – over 100,000 consumers viewing over 450,000 banners on CNET.com. (Previously published morphing evaluations evaluated morphing website characteristics and were based on predictive simulations using only priming-study data.) On relevant webpages, CNET's click-through rates almost double relative to control banners. We supplement the CNET field test with a focused experiment on an automotive information-and-recommendation website. The focused experiment replaces automated learning with a longitudinal design which tests the premise of morph-to-segment matching. Banners matched to cognitive styles, as well as the stage of the consumer's buying process and body-type preference, significantly increase click-through rates, brand consideration, and purchase likelihood relative to a control.

Keywords: *On-line advertising, banner advertising, behavioral targeting, website morphing, cognitive styles, field experiments, electronic marketing, dynamic programming, bandit problems, optimization of marketing.*

1. Introduction

This paper describes the first random-assignment field test of morphing with a sample size sufficient to observe steady-state behavior (116,168 unique CNET consumers receiving 451,524 banner advertisements). A banner advertisement morphs when it changes dynamically to match cognitive-style segments which, in turn, are inferred from consumers' clickstream choices. The website automatically determines the best "morph" for a segment by solving a dynamic program that balances exploration (trying new "morphs" to learn their effectiveness) and exploitation (using advertisements based on current expected outcomes). Advertising morphing modifies methods used in website morphing (Hauser, Urban, Liberali and Braun [HULB], 2009), which changes the look and feel of a website based on inferred cognitive styles. In HULB, cognitive-style segments varied on inferred styles such as impulsive vs. deliberative and analytic/visual vs. holistic/verbal.

HULB projected a 20% improvement in sales for BT Group's broadband-sales website, but their projections were based on simulated consumers who behaved according to clickstream preferences and morph x segment probabilities estimated in a priming study. HULB did not have the resources to obtain sufficient *in vivo* sample to field-test website morphing.[1] (By *in vivo* we refer to websites visited by consumers for information search or purchasing. By *in vitro* we refer to experiments in which we gather information from a panel of consumers. *In vitro* experiments attempt to mimic *in vivo* field experiments, but never perfectly.)

Large test samples are necessary *in vivo* because online morphing is designed for high-traffic websites with tens of thousands of consumers visiting. High traffic websites value sales from the $n+1^{st}$ consumer almost as much as sales from the n^{th} customer, hence the optimal so-

[1] Hauser, Urban and Liberali (2012) report a field test of website-morphing, but with a small sample. Their results are suggestive but not significant. The morphing algorithm may not have reached steady-state on their sample.

lution to the dynamic program often includes exploration well past the thousandth consumer per segment. (Technically, the need for so many observations is driven by the relative value of sales from $n + 1^{st}$ customer as compared to sales to the n^{th} customer.) With sixteen consumer segments, HULB estimated a need for 40,000 consumers to realize substantial gains from morphing (HULB, Figure 3, p. 209).

This first field test of banner morphing is promising. We observe an 83-97% lift in click-through rates between test and control cells when banners appear on websites that are highly relevant to consumers. This is substantially more than simply placing banners on relevant webpages as in behavioral-context targeting.

Click-through rates are an industry standard often used to judge banner effectiveness, but some managers also seek brand consideration and purchase likelihood. To examine these dependent measures, we supplement the large-sample field test with a smaller-sample random-assignment *in vitro* test of banner-to-segment matching on an automotive information-and-review website. We match banners to consumer segments defined by cognitive styles as well as buying-process stages and body-type preference. We avoid the need for extremely large samples with three longitudinal surveys in which the first two surveys measure advertising preference, cognitive styles, and stage of buying process. In a third survey, separated from the pre-measures by four and one-half (4½) weeks, consumers see banner advertising while searching for information on automobiles and trucks. The sample (588 consumers) is sufficient because we substitute direct measurement for Bayesian inference of segments and for optimal assignment by a dynamic program. *In vitro* measurement enables us to examine the fundamental premise that morph-to-segment matching improves brand consideration and purchase likelihood.

2. Banner Advertising – Current Practice

A banner advertisement is a paid advertisement that appears on a webpage. In the last ten years online advertising revenue has tripled. Banner advertisements account for 24% of online advertising revenue – about $6.2 billion in 2010. Banner advertisements cost roughly $10 per thousand impressions. Click-through rates are low and falling from 0.005 click-throughs per impression in 2001 to 0.001 in 2010 (PricewaterhouseCoopers 2011, Dahlen 2001). Conversion after click-through varies from 1% to 30% with an average of 2 to 4% (Nielsen 2008; Peterson 2009). As a result managerial interest is high for methods that improve banner effectiveness.

Current theory and practice attempts to increase click-through rates with a variety of methods. The simplest method uses experiments on a training sample to find the best combination of banner features. For example, Sundar and Kalyanaraman (2004) use laboratory methods to examine the effect of the speed and order of animation. Gatarski (2002) uses a genetic algorithm to search 40 binary features to achieve a 66% lift above a 1% click-through rate based on sixteen "generations" seeing approximately 200,000 impressions.

Iyer, Soberman and Villas-Boas (2005) and Kenny and Marshall (2000) suggest that click-through rates should improve when banners appear on webpages deemed to be relevant to consumers. Early attempts matched textual context, e.g., "divorce" in a banner to "divorce" on the webpage, but often had trouble distinguishing context, e.g., placing a banner for a divorce lawyer on a gossip account of Christina Aguilera's divorce (Joshi, Bagherjaeiran and Ratnaparkni 2011). Context matching improved when demographics and click logs were used to match relevant [banner] characteristics to consumers demographics, geographic location, and prior consumption. In a related application to Yahoo!'s news articles rather than banners, Chu, et al. (2009) use to increase click-through rates dramatically. Such context targeting is quite common.

For example, General Motors pays Kelly Blue Book to show a banner advertisement for the Chevrolet Sonic when a consumer clicks on the compact-car category.

Relevance can also be based on past behavior. "Behavioral targeting leverages historical user behavior to select the most relevant ads to display (Chan, Pavlov and Canny 2009, p. 209)." These researchers use cookie-based observation of 150,000 prior banners, webpages, and queries to identify which consumers are most likely to respond to banners. They report expected lifts of approximately 26%.

Finally, laboratory experiments manipulate consumers' goals (surfing the web vs. seeking information) to demonstrate that banner characteristics such as size and animation are more or less effective depending upon consumers' goals (Li and Bukovac 1999; Stanaland and Tan 2010). This web-based research is related to classic advertising research that suggests advertising quality and endorser expertise (likability) are more or less effective depending upon relevance (involvement) for consumers (e.g., Chaiken 1980; Petty, Cacioppo and Schumann 1983).

Morphing differs from prior research in many ways. First, matching is based on cognitive styles rather than context relevance or past behavior. Second, cognitive-style segments are inferred automatically from the clickstream rather than manipulated (as in surfer vs. seeker research). Third, morphing learns (near) optimally by trading off exploration versus exploitation to identify automatically morph-to-segment matches. Banner morphing is a complement to context or behavioral targeting. For example, morphing to match cognitive-style might be more effective on webpages that are relevant to consumers.

3. Brief Review of Banner Morphing

The fundamental behavioral premise of banner morphing is that a banner advertisement is more effective when it is customized for a cognitive-style segment. Given this premise, an online morphing system must accomplish two tasks to succeed. First, we must assign a consumer to a segment based on observing the consumer's clickstream. Second, we must learn the best banner(s) to assign to each consumer segment. We describe briefly how HULB's morphing algorithms accomplish these tasks. Readers familiar with HULB may wish to skip to §4.

3.1. Assigning Consumers to Segments based on Clickstream Data

We identify segments with a small-sample priming study. For example, HULB asked 835 broadband consumers to complete a survey in which they answered 13 questions about their cognitive styles, questions such as "I prefer to read text rather than listen to a lecture." HULB factor analyzed answers to the questions to identify four ipsative cognitive-style dimensions,. Median splits on the cognitive dimensions identified sixteen (2x2x2x2) cognitive-style segments.

By observing clicks as consumers explore the priming website, we develop a model that enables us to assign consumers to segments based on the clicks that consumers choose. For example, when faced with multiple click choices, we might observe that analytic/visual consumers are more likely than consumers in other segments to choose a tool that enables them to compare broadband plans. When this is true it is natural to use Bayesian methods to infer the probability that a consumer is analytic/visual when the consumer chooses that tool.

Following HULB, let r index consumer segments, m index alternative banner advertisements ("morphs"), n index consumers, t index clicks, and j index the various places on a webpage where a consumer might click (called click alternatives). Let r_n be consumer n's segment and $c_{ntj} = 1$ indicate that consumer n chose click alternative j on the t^{th} click. Let $\vec{c}_{nT}$ be consumer n's clicks up to and including the T^{th} click. We decompose each click alternative into a vector of characteristics, $\vec{x}_{jtn}$. Click characteristics can be dummy variables for areas of website (such as a comparison tool), expectations (click is expected to lead to graphics), or other descriptions. We observe clicks, click characteristics, and consumers' segments in a priming study and use the priming-study data to estimate click-characteristic preferences, $\vec{\omega}_r$, for each segment (logit likelihood, details in HULB, p. 211). The estimated preferences enable us to assign a utility, $\vec{x}'_{jtn}\vec{\omega}_r$, to each click alternative and to form the likelihood of observing $\vec{c}_{nT}$. With this likelihood, $\Pr(\vec{c}_{nt}|r_n = r)$, prior beliefs, $\Pr_0(r_n = r)$, and Bayes' Theorem, we estimate the probability, $\Pr(r_n = r|\vec{c}_{nt})$, that consumer n belongs to segment r. We summarize the mathematical details and all notation in Appendix 1.

HULB fix the time to morph, t_o, exogenously. For website morphing they set $t_o = 10$ clicks. We follow their strategy of a fixed time to morph. More complex algorithms have been proposed to determine the optimal time to morph (Hauser, Urban and Liberali 2012), but these algorithms were not available at the time of our experiments. Thus our experiments are conservative because morphing would likely do even better with improved algorithms.

3.2. Learning the Best Banner Advertisement for a Consumer Segment

Let p_{rm} be the probability of a good outcome (a sale, brand consideration, or a click-through) given a consumer in segment r experienced morph m for all clicks after t_o. One suboptimal method to estimate p_{rm}would be to assign morphs randomly to a large number, N_{large}, of consumers and observe outcomes. This strategy, similar to that used by Google's web optimizer and many behavioral or context targeting algorithms, is sub-optimal during the calibration period because N_{large} consumers experience morphs that may not lead to the best outcomes. A larger N_{large}, perhaps because the application requires that the p_{rm} be estimated with greater precision, would mean even more consumers need to be given suboptimal banners.

We minimize opportunity loss during the calibration period by solving a dynamic program that balances the opportunity loss incurred while exploring new morph-to-segment assignments with the knowledge gained about the p_{rm}'s. This knowledge enables us to assign morphs more effectively to future consumers. To solve the dynamic program we parameterize the distributions that summarize our uncertainty about the p_{rm}'s and use observed outcomes to update the posterior distributions. (The updating equations are in Appendix 1).

When we know a consumer's segment, the solution to the dynamic program has a simple form. Compute an index independently for each segment x morph combination. Call this index the Gittins' index, G_{rmn}. For the n^{th} consumer (in segment r), assign the morph, m^*, which has the largest index. The important and surprising result is that this simple strategy is the optimal solution to the dynamic program (Gittins 1979).

When we infer the consumer's segment, we use the expected value of Gittins' index, $EG_{mn} = \sum_r \Pr(r_n = r \mid \vec{c}_{nt}) G_{rmn}$ to choose the best morph. The expected-Gittins'-index solution is not optimal, but it is extremely close to optimal (Krishnamurthy and Mickova 1999). Because $G_{rmn} \rightarrow p_{rm}$ as $n \rightarrow \infty$, Gittins' index converges to the true segment x morph probabilities. The key difference between the expected-Gittins'-index strategy and the naïve calibration-sample strategy (N_{large}) is that the expected Gittins' strategy (1) learns while minimizing opportunity loss, (2) continues to learn as n gets large, and (3) can adapt when p_{rm} changes due to unobserved shocks such as changes in tastes, new product introductions, or competitive actions. Recalibration is automatic and optimal.

4. CNET Field Experiment

4.1. Smart Phone Banners on CNET.com

CNET.com is a high-volume website that provides news and reviews for high-tech products such as smart phones, computers, televisions, and digital cameras (about 4,300 annual reviews). It has 8 million visitors per day and has a total market valuation of $1.8 billion (Barr

2008). Banner advertising plays a major role in CNET's business model. Targeted banners demand premium prices. For example, a computer manufacturer might purchase banner impressions on web pages that provide laptop reviews. Non-targeted banners are priced lower and placed on less-valuable web pages. Morphing provides an improved method by which CNET can automate and optimize morph-to-segment targeting to provide higher value to its customers. CNET accepted our proposal to compare the performance of morphing versus a control on their website. They were also interested in any complementarities with behavioral or context targeting.

The banner context was AT&T smart phones. Consumers visiting CNET.com were assigned randomly to test and control cells. To assure sufficient sample for the morphing algorithm to converge, we assigned 70% of the consumers to the test cell. CNET's agency developed a pool of eight AT&T banner advertisements about HTC refurbished smart phones. (AT&T was out of stock on new HTC smart phones; AT&T followed industry practice to focus on refurbished smart phones when new phones were out of stock.) Industry experience suggests lower click-through rates for refurbished products, but the decrease should affect the test and control cells equally.

We tested eight potential banners which varied on characteristics likely to appeal differentially to consumers with different cognitive styles. In the control cell, the banners were assigned randomly. In the test cell, the morphing algorithm inferred each consumer's cognitive style and learned the best banner for each cognitive-style segment. Figure 1 provides the banners.

4.2. Cognitive Styles and Banner Characteristics

We first identified a candidate set of scale items from the literature (HULB and references therein; Novak and Hoffman 2009). Using the Greenfield Online panel, we asked 199 consumers to rate themselves on these scales. Factor analysis and scale purification identified eleven items likely to categorize CNET consumers. (Detailed scales and pre-study analyses are available from the authors.)

We next invited 1,292 CNET users to complete a short questionnaire using the eleven purified scale items. We factor analyzed these items to identify three factors which we labeled impulsive vs. deliberative, analytic vs. holistic, and instinctual vs. not. See Appendix 2. Following standard procedures (e.g., Churchill 1979), we re-purified these scales resulting in three multi-item ipsative cognitive-style dimensions with reliabilities of 0.75, 0.66, and 0.57, respectively. CNET felt they could target most effectively consumer segments that varied on the two most-reliable cognitive-style dimensions. Following HULB's methods, the morphing algorithm used four cognitive-style segments defined by median splits (2x2: impulsive vs. deliberative x analytic vs. holistic).

CNET's agency developed the eight banners, seven of which were targeted to cognitive styles. Because morphing automates morph-to-segment matching, the banner designers did not have to make the match themselves; they just had to assure sufficient variation among the banners. (The eighth banner, which did not end up best for any segment, was unconstrained by cognitive styles.) The banners varied on action-links ("learn more" vs. "get it now") and level of detail provided (list of features vs. links to video, etc.). CNET designers also varied the banners on characteristics they judged might appeal to different cognitive styles: font size, font color, background color, location, and shape. See Figure 1. CNET believed the eight banners had sufficient variation in potential appeal, sufficient for the morphing algorithm to find the best banner(s) for each consumer segment.

[Insert Figure 1 about here.]

4.3. Segment-Specific Click Preferences and Estimation of Segment-Membership

We decompose every click alternative into a vector of 22 click characteristics including dummy variables for areas on the homepage (carousal, navigation bar, promotion bar, more stories, popular topics, etc.), areas on other pages (product-specific reviews, CNET says, inside CNET, etc.), usage patterns (search category, social influences, tech-savvy news, etc.), and independent judges' evaluations of expected click outcomes (pictures, graphs, data, etc.). We estimate segment-specific click-characteristic preferences, $\vec{\omega}_r$, during the same priming study used to identify the segments (1,292 CNET users). The preference weights enable us to write the likelihood, $\Pr(\vec{c}_{nt}|r_n = r)$, for each consumer's clicks on the CNET website. Coupled with prior beliefs about segment membership, this likelihood is sufficient to compute the posterior probability, $\Pr(r_n = r|\vec{c}_{nt})$, that consumer n belongs to segment r. Details of the estimation of the $\vec{\omega}_r$ follow HULB. Parameter values are given in Appendix 3.

To address the fact that consumers make repeated visits to CNET, we define consumers as active or not active. An active consumer must make at least five clicks on tracked areas of the website. We use cookies so that updating continues through multiple visits when necessary. Five clicks give us sufficient observations to morph ($t_0 = 5$). In the control we track clicks but only to determine whether a consumer is active. Before becoming active, consumers are not shown any banners (neither in test nor control). After becoming active, test consumers see a banner selected by the morphing algorithm and control consumers see a randomly chosen banner.

4.4. Modifications to Handle Multiple Sessions

For website morphing HULB did not track repeat sessions, but for banner morphing repeat sessions are common (as tracked with cookies). The same banner might be shown in many sessions. CNET (and AT&T) consider the banner a success if the consumer clicks through in at least one session. We adopt that definition of success. To account for interrelated sessions, we use a strategy of temporary updates and potential reversals.

This is best illustrated with a three-session example. Suppose that a consumer sees the same banner in three sessions and clicks through in the second session. A naïve application of HULB would make three updates to the parameters of the posterior distributions for the success probabilities, p_{rm}. The updates would be based erroneously on observations of failure, success, failure. Instead, using CNET's success criterion, the correct posterior should be computed after the third session based on one success because the banners achieved their collective goal of at least one consumer click-through. Furthermore, until we reach the third session, updates should represent all information collected to that point. To achieve these goals we use the following up-dating strategy. After the first session (no click through), we update the posterior distribution based on a failure – this is the best information we have at the time. After the second session (click through), we reverse the failure update and update as if success. On the third session (no click through), we do nothing because the update already reflects a success on CNET's criterion. The mathematical formulae are given in Appendix 1.

Finally, the morphing algorithm requires that we set priors for the segment x morph click-through probabilities. HULB suggest that weakly-informative priors suffice. Our priors are equal for all morphs and set to the historic click-through probability for banners for refurbished smart phones. So that the priors are weakly informative, parameters of the prior distribution are selected based on an effective sample size of forty consumers – small compared to the anticipated number of CNET consumers.

4.5. Results of the CNET Field Experiment

CNET placed banners on their website for all active consumers in the test and control cells during April 11, 2011 to May 13, 2011. Naturally, there were other banners placed on CNET during the 31-day test period, but these banners were placed randomly between test and control. Both we and CNET went to great lengths to ensure there were no systematic effects of these banners or interactions with AT&T HTC advertising. Sampling appeared random – we detected no systematic differences in the placement of control banners across estimated cognitive-style segments ($\chi^2_{30} = 15.9, p = 0.98$).

Table 1 summarizes the field-test results. Overall, 116,168 consumers saw 451,524 banners. Some banners were placed on pages where any smart phone was rated, compared, priced, discussed, or pictured. Specifically, 32,084 consumers (27.4%) saw 58,899 targeted banners (13.0%). Morphing really shines when combined with such context targeting. Morphing achieves significant and substantial improvements for banners ($t = 3.0, p = 0.003$) and for consumers ($t = 2.2, p = 0.028$). In both cases, click-through rates almost doubled (83% and 97% lifts, respectively). To put this *in vivo* impact in perspective, targeting alone in the control cell did not achieve a significant lift for either banners ($t = 0.3, p = 0.803$) or consumers ($t = 1.4, p = 0.167$).

[Insert Table 1 about here.]

Table 1 also cautions that gains to morphing are not universal. There was no significant lift for banners or consumers when the banners were not on targeted webpages ($t = 0.5, p = 0.495$ and $t = 1.74, p = 0.081$, respectively). Significant gains were realized only when morphing was combined with targeting: interactions were significant for banners ($\chi^2 = 161.8, p < 0.01$) and for consumers ($\chi^2 = 8.2, p = 0.017$). Although there is drop among non-targeted banners, that drop is marginally significant at best. Morphing clearly interacts with targeting – an interaction worth further investigation with future *in vitro* experiments.

This interaction should not surprise us; we expect cognitive-style morphing to be more effective when the banner advertisements are targeted to webpages that are relevant to consumers' purchasing situations. Interactions of quality and source with relevance (involvement) have a long history in advertising research (Chaiken 1980,; Petty, Cacioppo and Schumann 1983) and are consistent with current prescriptive theories of targeting (Iyer, Soberman and Villas-Boas 2005; Kenny and Marshall 2000). To the extent that matching banners to cognitive styles facilitates preference learning, observed interactions between targeting and preference learning might be enhanced by morphing (Lambrecht and Tucker 2011).

The success of targeted cognitive-style morphing raises an interesting hypothesis. Banner morphing might have had an even larger lift if we had allowed the optimal morph to vary between targeted and non- targeted webpages. This hypothesis foreshadows our automotive experiment where we define segments by cognitive styles and buying stage and where we target all consumers by body-type preference.

5. Automotive Experiment to Test Matching Morphs to Segments

Because managers might be interested in metrics other than click-through rates, we supplement the CNET field experiment with an *in vitro* automotive experiment. (Organizational differences between CNET and AT&T, and proprietary concerns, made it impossible to track click-through rates back to sales of AT&T telephones.) In a focused automotive experiment we abstract from the mechanics of banner morphing (Gittins' learning) to test whether morph-to-segment matching increases brand consideration and purchase likelihood as well as click-through rates. This focused experiment enables us to test the fundamental behavioral hypothesis motivating banner morphing; an hypothesis that banner advertisements are more effective when targeted to consumer segments that vary on cognitive styles and, perhaps, other characteristics such as buying stage or body-type preferences.

Brand consideration and purchase likelihood are more-intrusive measures than click-through rates. To obtain these measures we invited consumers to complete questionnaires before and after searching for information on an automotive information-and-review website. Because a sample size of tens of thousands is not feasible with this design, we use longitudinal methods to effect matching. See Figure 2. In Phase 1, consumers rate all test and control advertisements for their buying-stage and preferred body-type. Two weeks later in Phase 2, consumers answer a series of scales that enable us to assign consumers to cognitive-style segments. In Phase 2 we also obtain pre-measures of brand consideration and purchase likelihood. Phases 1 and 2 replace the morphing algorithm with *in vitro* measurement. These phases enable us to assign each consumer to a segment and to identify the best banners for each segment. The experiment occurs two and one-half weeks later in Phase 3 (4½ weeks after rating banners), when consumers see banners while exploring an automotive information-and-review website. In the test cell banners are matched to cognitive styles (plus buying stage and body-type preference) while in the control cell banners are matched only to body-type preference. (Note that this experiment also extends the definition of consumer segment to include buying stage.)

[Insert Figure 2 about here.]

The experimental design, its implications, and potential threats to validity are best understood and evaluated within context. Thus, before we describe the Phase 3 experiment, we first describe the website, the automotive consumer segments, and the test and control banner advertisements.

5.1. Automotive Banners on an Information-and-Recommendation Website

Information and recommendation websites such as Edmunds', Kelley Blue Book, Cars.com, and AutoTrader, play a major role in automotive purchasing. For example, Urban and Hauser (2004) estimate that at least 62% of automotive buyers search online before buying a car or truck. Giffin and Richards (2011) estimate that 71% of automotive buyers search online and that online search was more influential in purchase decisions than referrals from family or friends, newspapers, and other media sources. Because information-and-recommendation websites attract potential purchasers, automotive manufacturers invest heavily in banner advertising on these websites. The importance of such expenditures motivated General Motors to test morph-to-segment-matching of banner advertising for their Chevrolet brand. General Motors' managerial motivation matched our scientific desire to test the premise of morph-to-segment matching.

We created a website that simulated consumer experience on information-and-recommendation websites. Figure 3 illustrates the landing page and an example search page. On the automotive website consumers could search for information, receive tips and reviews, learn about insurance, and read reviews just like they would on commercial information-and-recommendation websites. To mimic best practices all test and control banners were targeted by consumers' expressed preferences for one of five body types. Such targeting is typical on commercial websites as on Edmunds.com where body-type preference – coupe, convertible, sedan, SUV, etc. – is displayed prominently on the landing page. Body-type targeting enhances external validity but otherwise has no effect on the test-vs.-control comparisons.

[Insert Figure 3 about here.]

5.2. Cognitive Styles and Stage of the Automotive Buying Process

Body-type preference and the automotive buying process stage were measured in Phase 1; cognitive styles were measured in Phase 2. We defined buying-stage segments by: collection, comparison, or commitment. "Collection" segments included consumers who indicated they were more than a year away from buying a car or truck, but in the process of collecting information. “Comparison” segments included consumers less than a year away from buying a car or truck and who had already gathered information on specific vehicles or visited a dealer. “Commitment” segments included consumers who plan to purchase in the next three months, who have collected information on specific vehicles, and who have visited a dealer.

To identify cognitive styles we asked consumers to answer twenty-nine scales adapted from Novak and Hoffman (2009). We factor analyzed their answers to identify three factors. We labeled the first two factors as rational-vs.-intuitive and impulsive-vs.-deliberative. The third factor was hard to define. See Appendix 2. Following standard procedures (e.g., Churchill 1979), we purified the scales resulting in three multi-item cognitive-style dimensions with reliabilities of 0.87, 0.87, and 0.36, respectively. We selected the first two cognitive dimensions to define 2x2 consumer segments based on mean splits.[2,3]

5.3. Test and Control Banner Advertisements

We created test banners that varied on graphics, amount of content, and format to span the cognitive-style segments for each body type and buying stage. The designers sought to provide sufficient variation so that we could target the banners to each cognitive-style segment. Collection-targeted banners emphasize information; comparison-targeted banners compare targeted vehicles to competitors; and commitment-targeted banners stress test drives, finding a dealer, and purchase details. In total there were 75 test banners: (five designs to appeal to different cognitive styles) x (three information content designs to appeal to different stages of the buying process) x (five body types for targeting).

[2] Despite differences in the underlying scales, the type of consumer, and the buying context, the cognitive dimensions for high-tech consumers and automotive consumers are not dissimilar. For each set of consumers, one dimension is impulsive vs. deliberative. The other dimension is either analytic vs. holistic (high tech) or rational vs. intuitive (automotive). More experience might identify common dimensions that can be used across applications.

[3] In the automotive experiment we used mean-splits rather than median-splits to define segments. There is no reason to believe this will affect the results. Indeed, the two categorizations are quite similar. When we correct for the differences between median- and mean- splits, we the test group is still significantly better than the control group.

There were ten control banners: two banner advertisements for each of five body types. Control banners did not vary by cognitive style or buying stage. The control banners were the banners that Chevrolet was using on real information-and-recommendation websites at the time of the morph-to-segment-matching experiment. Figure 4 shows both control banners and all five test banners for one body type (two control and fifteen test banners).

[Insert Figure 4 about here.]

This control was most relevant to General Motors' business decisions, but if we are to use it as a scientific control we must establish it is a valid control. The literature uses a random selection of "morphs" as a no-morphing control. If the current banners are better than a random selection of test banners, then any differences between test and control cells would underestimate the gain due to morph-to-segment matching. We could then conclude that the improvement due to matching is at least as large as we measure. However, if current banners are worse than a random selection of test banners, then we could not rule out that the test banners are, on average, simply better than the control banners.

We use the Phase 1 banner evaluations to compare potential test and control banners on meaningfulness, relevance, information content, and believability. Using Phase 1 measures we create an average score that combines the meaningfulness, relevance, information content, and believability ratings. The average score for a test banner is 3.36 (out of 5); the average score for a control banner is 3.70. The combined control banners are significantly larger than a randomization of test banners ($t = 10.3, p < 0.01$). Even if we were to use only the two best test banners for all consumers, the average score is still less than the control score ($t = 2.7, p < 0.01$). We therefore conclude that the current Chevrolet banners are a sufficient control. If morph-to-segment matching is superior to the current Chevrolet banners then it is highly likely that morph-to-segment matching will be superior to either a randomly-selected set of test banners or to a non-matched mix of the two best test banners.

5.4. Experimental Design and Dependent Measures

In Phase 3 consumers were invited to explore an information-and-recommendation website called "Consumer Research Power." Consumers search naturally as if they were gathering information for a potential automotive purchase. They do so for a minimum of five minutes. While consumers searched we recorded click-through on the banners. During this search we placed banner advertisements for Chevrolet models as they would be placed in a natural setting. Test consumers received banners that alternated between the best and second-best banner for their cognitive-style segment where best was defined by the average over consumers in a cognitive-style segment of the Phase 1 measures (meaningfulness, relevance, information content, and believability). Test banners were also targeted by buying stage. Control consumers received banners that alternate between the two control Chevrolet banners.[4] All banners, both test and control, were targeted by body-type preference.

After consumers complete their search on "Consumer Research Power," we measure Chevrolet brand consideration and purchase likelihood. Dependent measures include click-through rates for banners, click-through rates per consumer, post-measures of brand consideration and purchase likelihood, and the difference in brand consideration and purchase likelihood between the post-measures (after Phase 3) and the pre-measures (during Phase 2).

5.5. Potential Threats to Validity

One potential threat to validity is that exposure to banners in Phase 1 might have conta-

[4] Control consumers also received a more-general banner on the landing page. This more-general banner mimics *in vivo* practice. When we include the more-general banner in our analyses, the exposure-weighted rating of all control banners (3.75) remains significantly better than the exposure-weighted rating of the test banners (3.46) reaffirming the control as a valid control ($t = 3.0, p < 0.01$). To be conservative, we do not include clicks from landing-page banners for either the test or control cells.

minated the Phase 3 measures. We took steps to minimize this threat. The Phase 1 questionnaire is relatively short (five minutes) and occurs 4½ weeks before the Phase 3 experiment. In Phase 1 consumers are not allowed to click through on the banners and, hence, do not receive the same rich information experience as in Phase 3. Instructions were written carefully to disguise the goals of the later phases – consumers believed the Phase 3 website experience was a test of the website not an advertising test. We believe that the time delay, the number of banners rated, the lack of active click-through in Phase 1, and instructions that disguised later phases combine to limit contamination from Phase 1 to Phase 3.

More importantly, the experimental design minimizes potential false positives that might be due to contamination. First, Phase 2 is more proximate in time than Phase 3. Contamination, if any, should be larger in Phase 2 than in Phase 3, making it more difficult to show an effect on Phase-3-vs.-Phase-2 measures. Second, contamination, if any, would affect test and control cells equally and have no impact on statistical tests of differences that are invariant with respect to constant effects.

Another potential threat to validity is that the morph-to-segment test chooses from more banners than the control. If a consumer saw a greater variety of banners in the test cell, then we would be concerned about biases due to wear-out in the control cell or biases because of greater variety in the test cell. All else equal, greater variety in the banners that a consumer actually sees increases the odds that a banner is the best banner for a consumer. Our design minimizes this threat because each consumer sees two body-type-targeted banners in the test cell and two body-type-targeted banners in the control cell.

5.6. Results of the Automotive Experiment Testing the Behavioral Premise of Morphing

We invited 2,292 members of the Gongos Automotive Panel to participate in a multiphase study of website design. Consumers were screened to be either an equal or sole decision maker in automotive purchases and plan to purchase a new car or truck in less than three years. This mimics standard practice. Of these, 1,299 consumers agreed to participate (61% response rate) and 588 consumers completed Phases 1, 2 and 3 (45.3% completion rate). More consumers were assigned to the test cell (70%) than the control cell (30%) so that we had sufficiently many consumers in each consumer segment. All statistical tests take unequal cell sizes into account.

5.7. Test-vs.-Control Analyses (Post Only)

Because the pre-conditions were the same in the test and control cells, we begin with post-only results. Table 2 reports the post-only comparisons for the morph-to-segment-matching experiment. As in the CNET field experiment (on targeted webpages), the lift in click-through rates is significant. The test-vs.-control difference in click-through rates is significant whether we focus on impressions (245% lift, $t = 3.3, p < 0.01$) or consumers (66% lift, $t = 4.4, p < 0.01$). The automotive experiment enables us to look beyond click-through rates to brand consideration and purchase likelihood. Both measures increase significantly based on morph-to-segment matching with consideration the most substantial (30% lift, $t = 4.9, p < 0.01$ and 8% lift, $t = 4.1, p < 0.01$, respectively).

[Insert Table 2 about here.]

5.8. Test-vs.-Control and Pre-vs.-Post Analyses

We increase statistical power by accounting for the pre-measures (as in differences of differences) and for variation in segment membership or demographics due to stochastic variation in random assignment. Table 3 reports the results where we control for pre-measures, segment membership, and demographics. Click-through and brand consideration are quantal measures (click or not; consider or not), therefore we use a logit formulation for these measures. Purchase likelihood is a scaled measure, so a regression suffices. Click-through (all banners) and brand consideration are significant at the $p < 0.01$ level and purchase likelihood is significant at the $p = 0.02$ level. Click-through (per consumer) is marginally significant at the $p = 0.06$ level.

[Insert Table 3 about here.]

In Table 3 we used the pre-measure as an independent variable because the pre-measure accounts for both measurement error and, partially, for unobserved heterogeneity in consumers' propensity to consider or purchase Chevrolet. We can also remove unobserved heterogeneity with double-difference formulations. When we do so, test vs. control is significant at the 0.01 level for both brand consideration and purchase likelihood (details from the authors).

Together Tables 2 and 3 suggest that morph-to-segment matching increases brand consideration and purchase likelihood (for automotive consumers) as well as click-through rates. When combined with the CNET field experiment, the focused automotive experiment suggests that the effectiveness of banners is improved when morphing targets banners to consumers segments that vary on cognitive styles and behavioral-context characteristics (buying stage and body-type preference). Both experimental results (CNET and automotive) reinforce the priming-study-based simulations reported in HULB for website morphing.

6. Implications and Future Directions

Online morphing is a nascent, but promising, technology for improving the effectiveness of banner advertising and website design. The original website morphing paper established the potential for increasing sales if websites morphed their look and feel, but the evaluation was based on data generated in a priming study. A subsequent field application tested website morphing for a Suruga Bank website (Hauser, Urban and Liberali 2011). The Suruga Bank results were also promising, but the small sample was not sufficient to test fully whether the expected Gittins' index would converge to the best morph.

This paper provides experimental data for morphing banner advertisements. The CNET field experiment establishes that an expected-Gittins'-index strategy enables a website to learn automatically the best morph for each consumer segment. Click-through rates improve substantially for targeted webpages on a high-traffic website. The automotive experiment tests the fundamental premise of matching morphs to consumer segments. Morph-to-segment matching improves click-through rates, brand consideration, and purchase likelihood. (The automotive experiment assumes the CNET result that, in steady state, the expected-Gittins'-index strategy would identify the best morph-to-segment matches.)

The four tests of morphing to date (two for website morphing, two for banner morphing) are promising. The expected-Gittins'-index provides near optimal learning; we know of no better strategy. By the principle of optimality, the expected-Gittins'-index strategy is superior to a strategy that relies on setting aside the first N_{large} consumers for a random-assignment experiment. Given the high traffic on these websites and the low click-through rates, the improvement can be substantial. However, the current state of the art for morphing still requires a priming study to (1) establish the definitions of consumer segments and (2) obtain data on click preferences for each segment (the $\vec{\omega}_r$).

6.1. Norms Rather than Priming Studies

We envision future applications that rely on norms rather than priming studies. For example, in the four applications to date the definitions of the cognitive-style segments are somewhat similar. With more applications, we might use meta-analyses to stabilize cognitive-style definitions so that they might be used without a priming study. Similarly, meta analyses might provide strong priors for segment-based click-characteristic preferences, $\vec{\omega}_r$. We might also identify the click-alternative characteristics that best distinguish consumer segments. Such empirical generalizations would enable an advertiser to rely on norms or an abridged priming study. This diffusion of knowledge has already taken place in pre-test markets for consumer packaged goods. Initial studies explored the methods, but later studies built the normative databases. Today, most new product forecasts rely on norms. When norms become established we expect morphing to flourish.

6.2. Practical Challenges

The banner-morphing experiments in this paper, and the prior website-morphing tests, relied on experienced professional designers to develop banners or websites to match consumer segments. Morphing implementation identified the best banners for each segment which often spurred further creative development. As we gain more experience we expect that scientific studies will lead to greater insight into the design challenge. Such studies are fertile grounds for new research. The other practical challenge is transportable code. All code has been specific to the application (and open source). Conjoint analysis, hierarchical Bayes, multinomial logit analyses, and other marketing science methods diffused widely when generalized software became available. We hope for the same diffusion with banner and website morphing.

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Table 1
CNET Field Test of Banner Advertisement Morphing

	Sample Size		Click-through Rate [a]			Signif-icance
	Test	Control	Test	Control	Lift	
Targeted webpages						
All banners	40,993	17,906	0.307 [b]	0.168	+ 83%	0.003
Per consumer	22,376	9,708	0.250 [b]	0.127	+ 97%	0.028
Non-targeted webpages						
All banners	262,911	129,714	0.151	0.160	- 6%	0.495
Per consumer	59,362	24,722	0.144 [c]	0.197	- 27%	0.081

[a] Click-through rates are given as fractions of a percent, e.g., 0.307 of 1%.

[b] Test cell has a significantly larger click-through rate than control cell at the 0.05 level or better.

[c] Test cell has a marginally significantly smaller click-through rate than the control cell at the 0.10 level.

Table 2
Automotive Experiment: Banner Advertisement Morphing (Post-only Results)
(All banners are targeted by body-type preference.)

	Sample Size		Outcome Measure [a]			Signif-icance
	Test	Control	Test	Control	Lift	
Click-through rates						
All banners	6,348	2,643	0.97% [b]	0.26%	+ 245%	< 0.01
Per consumer	421	167	15.9% [b]	9.6%	+ 66%	< 0.01
Brand Consideration	421	167	42.8% [b]	32.9%	+ 30%	< 0.01
Purchase likelihood	421	167	3.28 [b]	3.05	+ 8%	< 0.01

[a] Click-through rates are given as percents. Consideration is a consider-or-not measure reported as a percent. Purchase likelihood is measured with a five-point scale.

[b] Test cell has a significantly larger at the 0.01 level.

Table 3
Automotive Experiment: Banner Advertisement Morphing
Controlling for Pre-measures, Segment Membership, and Demographics

	Click-through All Banners		Click-thru per Consumer		Brand Consideration		Purchase Likelihood	
	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Intercept	-7.400	< 0.01	-3.559 [a]	< 0.01	-4.172 [a]	< 0.01	0.086	0.686
Test vs. control treatment	1.244 [a]	< 0.01	0.562 [b]	0.062	0.756 [a]	< 0.01	0.194 [a]	0.016
Pre-measure	—	—	—	—	3.568 [a]	< 0.01	0.785 [a]	< 0.01
Buying-process dummies								
Collect	0.368	0.388	0.553	0.144	0.787 [a]	0.023	0.352 [a]	< 0.01
Compare	0.762 [a]	< 0.01	0.984	< 0.01	0.510 [b]	0.062	0.108	0.188
Commit	—	—	—	—	—	—	—	—
Cognitive-dimension dummies								
Rational	0.405	0.112	0.184	0.462	0.538 [a]	0.027	-0.001	0.989
Intuitive	—	—	—	—	—	—	—	—
Impulsive	0.187	0.485	0.176	0.496	0.271	0.277	0.132 [b]	0.083
Deliberative	—	—	—	—	—	—	—	—
Male (vs. Female)	-0.463 [b]	0.070	-0.329	0.184	0.274	0.259	0.074	0.313
Age	0.022	0.052	0.020 [b]	0.056	0.014	0.184	0.006 [b]	0.064
Income	0.000	0.905	-0.002	0.429	-0.002	0.482	-0.000	0.785
Log-likelihood ratio	-367.916 [a]		-223.039 [a]		-232.057 [a]		-734.371 [a]	

[a] Significant at the 0.05 level. [b] Significant at the 0.10 level. Sample size 8.991 impressions or 588 consumers. All equations significant at the 0.01 level.
Test vs. control is also significant at the 0.01 level with a differences of differences specification.

Figure 1
Eight Banner Advertisements Targeted to Cognitive Styles (CNET Field Experiment)

All ads had the word 'refurbished'

Figure 2
Automotive Experiment: Longitudinal Design to Effect Morph-to-Segment Matching

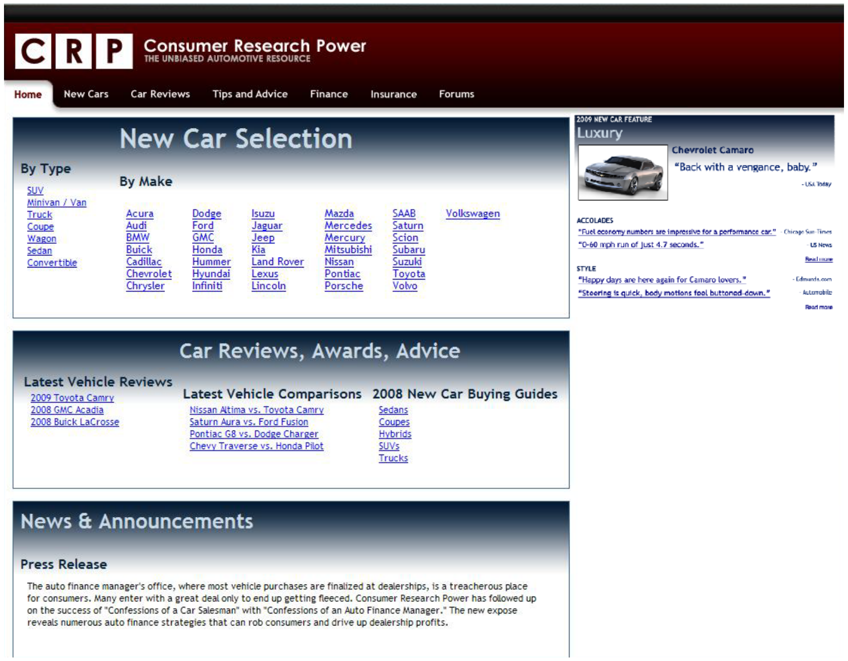
Phase 1
Develop potential banners based on pre-studies.
Screen consumers for target market
Consumers indicate body-type preference.
Consumers indicate stage of buying process.
Consumers rate potential banners on meaningfulness, relevance, information content, and believability.
5 minutes

Phase 2 (Two weeks later)
Consumers complete 29 cognitive-style scales.
Pre-measures for consideration and purchase likelihood.
10 minutes

Factor analyze cognitive-style scales. Assign consumers to cognitive-style segments and buying stage. Identify the best "morphs" for each cognitive-style segment. All banners are targeted by body type.

Phase 3 (experiment, four and one-half weeks after Phase 1)
Consumers explore "Consumer Research Power" website.
Consumers exposed to banners in natural search.
Test: Banners assigned by morph-to-segment rules.
Control: Current *in vivo* Chevrolet banners.
Post-measures for consideration and purchase likelihood.
20 minutes

Figure 3
Simulated Website for Automotive Experiment Matching Morphs to Segments
(Landing page on the left. One of many subsequent pages on the right.)



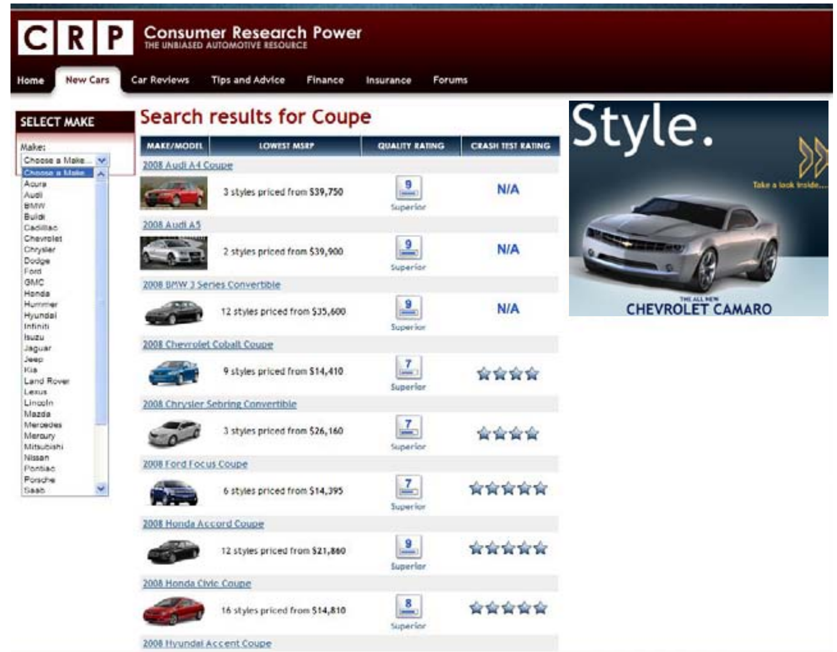
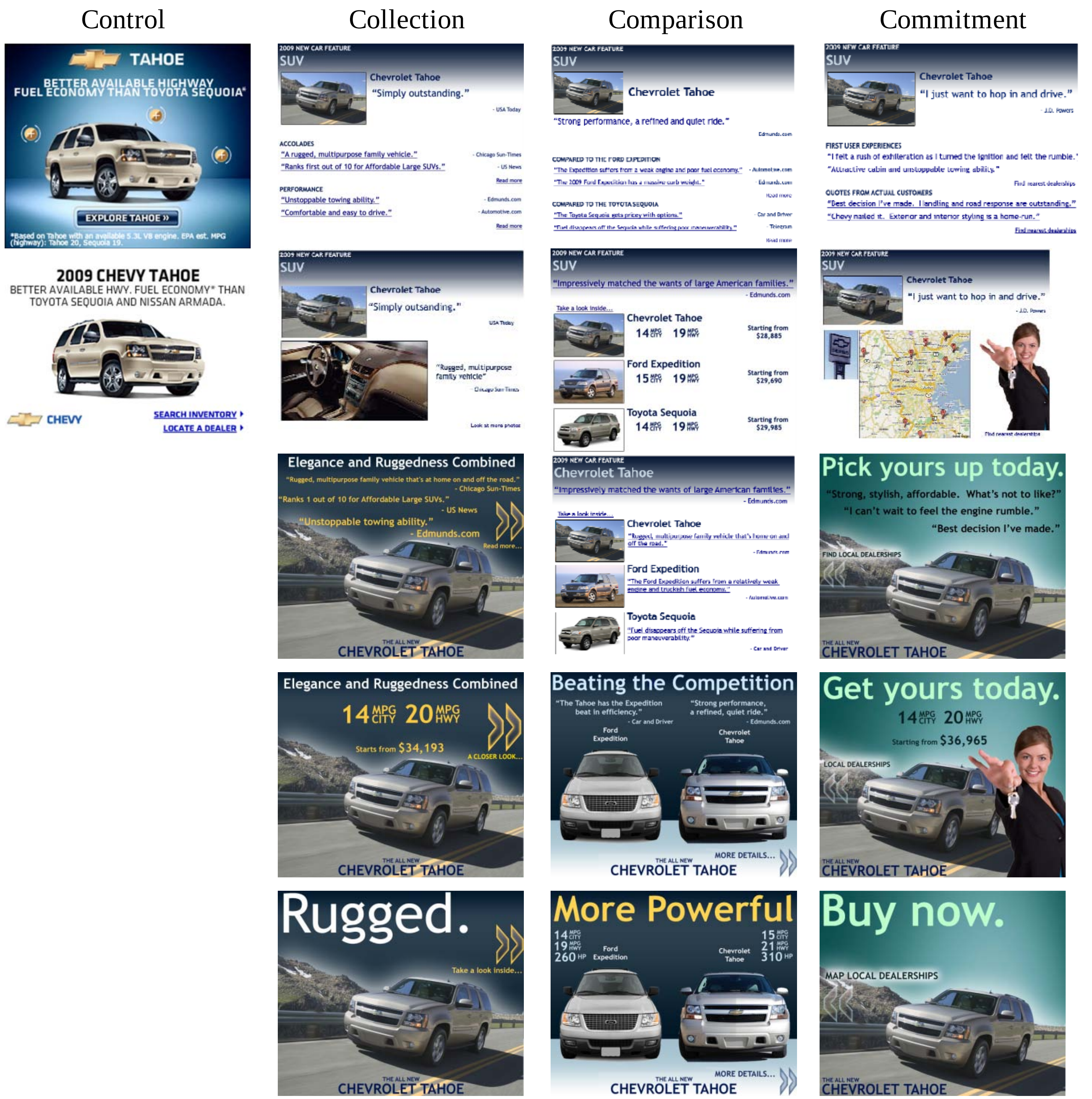


Figure 4

Example Test and Control Banner Advertisements for the Automotive Experiment

(The left-most banners are controls. The other columns are five banners for each buying-stage segment. In the experiment there were 10 potential control banners: body type x two banners. There were 75 potential test banners: body type x buying-stage x cognitive-style.)



Appendix 1. Mathematical Summary of Morphing Algorithm

A1.1. Notation

Let n index consumers, r index consumer segments, m index morphs, t index clicks, j index click alternatives. Capital letters indicate totals. Let $c_{ntj} = 1$ if n chooses the j^{th} click alternative on the t^{th} click and $c_{ntj} = 0$ otherwise. Let $\delta_{mn} = 1$ if we observe a positive outcome when n sees morph m, and $\delta_{mn} = 0$ otherwise. Let $\vec{c}_{nT}$ be the vector of the c_{ntj} up to an including T^{th} click, let $\vec{x}_{jtn}$ be the vector of characteristics of the j^{th} click alternative for the t^{th} click for consumer n, let $\vec{\omega}_r$ be the vector of preference weights for the $\vec{x}_{jtn}$ for the r^{th} segment, let $\Pr_0(r_n = r)$ be the prior probability that n is in segment r, let q_{rn} be the probability that n belongs to segment r, let p_{rm} be the probability of observing an outcome (sale, click-through, etc.) if a consumer in segment r sees morph m, let G_{rm} be Gittins' index for r and m, and let a be the consumer-to-consumer discount rate.

A1.2. Assigning Consumers to Segments

We first estimate the $\vec{\omega}_r$ from a priming study in which consumers complete scales to identify their segments and we observe the click alternatives they choose. The estimation is based on a logit likelihood with either maximum-likelihood or Bayesian methods. Details are standard, available in HULB, and not repeated here. For online morphing we know the $\vec{x}_{jtn}$'s for key click alternatives, hence $\vec{x}'_{jtn}\vec{\omega}_r$, which is n's observed utility for the j^{th} click alternative for the t^{th} click. Using the logit likelihood (HULB, p. 211), we obtain the probability that observed clicks are chosen given that the consumer is in segment r. Bayes Theorem provides q_{rn}.

(A1)

$$\Pr(\vec{c}_{nT}|\vec{\omega}_r, \vec{x}_{jkn}s) = \Pr(\vec{c}_{nT}|r_n = r) = \prod_{t=1}^{T}\prod_{j=1}^{J_k}\left(\frac{\exp[\vec{x}'_{jtn}\vec{\omega}_r]}{\sum_{\ell=1}^{J_k}\exp[\vec{x}'_{\ell tn}\vec{\omega}_r]}\right)^{c_{ntj}}$$

$$q_{rn} = \Pr(r_n = r|\vec{c}_{nT}) = \frac{\Pr\{\vec{c}_{nT}|r_n = r)\Pr_0(r_n = r)}{\sum_{s=1}^{R}\Pr\{\vec{c}_{nT}|r_n = s)\Pr_0(r_n = s)}$$

A.1.3. Updating Beliefs about the Probability of an Outcome Given a Morph and Segment

After observing outcomes for each consumer, n, we update our beliefs about outcome probabilities. Call these probabilities p_{rmn}. Using beta-binomial updating we represent posterior knowledge about these probabilities with a beta distribution with parameters α_{rmn} and β_{rmn}. If we knew the consumer's segment with certainty, we could update these parameters with standard formulae. However, segment membership is only partially observable, hence we use pseudo-likelihood updating:

(A2)

$$\alpha_{rmn} = \alpha_{rm,n-1} + \delta_{mn}q_{rn}$$

$$\beta_{rmn} = \beta_{rm,n-1} + (1 - \delta_{mn})q_{rn}$$

Equation A2 suffices for website morphing, but for banner morphing the relevant criterion is at least one click-through per consumer. For this criterion we take multiple sessions into account. In banner morphing we use Equation A2 at the end of the first session of a new consumer. Subsequently, if the any prior outcome was a success ($\delta_{mn} = 1$), we do nothing. If all prior outcomes were failures ($\delta_{mn} = 0$) and we observe a failure we do nothing. If all prior outcomes were failures ($\delta_{mn} = 0$) and we now observe a success ($\delta_{mn} = 1$), we reverse the update. Prior failures did not change the α_{rmn}'s for each r, so we now add q_{rm}. When a failure becomes a success, we undo the update that was added to the β_{rmn}'s for each r. Earlier failures caused us to add q_{rn} for each r to the β_{rmn}'s, hence we now subtract q_{rn} for each r from the β_{rmn}'s.

A.1.4. Calculating the Gittins' Index for Each Morph and Segment

First assume the consumer's segment is known. Gittins' Index Theorem enables us to decompose a dynamic program over M morphs into M much simpler dynamic programs. The long-run optimal strategy is to choose in each period the morph with the largest index in that period. Gittins' index provides the needed metric for each uncertain morph by comparing it to a fixed option with a probability, G_{rm}, of a positive outcome. Bellman's equation for the morph-and-segment specific dynamic program is given as follows. (Details in HULB p. 207-208 and Gittins 1979.) In this equation, $R(\alpha_{rmn}, \beta_{rmn}, a)$ is Bellman's value function. We solve this equation for fixed points to table G_{rm} as a function of α_{rmn} and β_{rmn}. (a is fixed.)

(A3) $$R(\alpha_{rmn}, \beta_{rmn}, a) = \max\left\{ \frac{G_{rmn}}{1-a}, \quad \begin{array}{r} \dfrac{\alpha_{rmn}}{\alpha_{rmn}+\beta_{rmn}}[1 + aR(\alpha_{rmn}+1, \beta_{rmn}, a)] \\ + \dfrac{\alpha_{rmn}}{\alpha_{rmn}+\beta_{rmn}} aR(\alpha_{rmn}, \beta_{rmn}+1, a) \end{array} \right\}$$

A.1.5. Choosing the Morph in Each Period

When segment assignments are stochastic, we chose the morph in each period that has the highest value for the expected Gittins' index, EG_{mn}. This is the (near) optimal strategy to minimize opportunity loss.

(A4) $$EG_{mn} = \sum_{r=1}^{R} q_{rn} G_{rmn}(\alpha_{rmn}, \beta_{rmn})$$

Appendix 2. Factor Loadings Matrices for CNET and Automotive Experiments

We factor analyze consumers' self-evaluations on cognitive-style items using principle component analysis and varimax rotation with Kaiser normalization retaining factors with eigen-values greater than one. We interpret the factors based on the factor loadings and then use scale purification with Cronbach's alpha to select scale items (Churchill 1979). Segments are based on retained scales (sufficient reliability). In the priming study consumers are assigned to segments based on median splits (CNET) or mean-splits (automotive) of sum scores.

A2.1. Cognitive-Style Factor Loadings for CNET Field Experiment

	Impulsive vs. Deliberative	Analytic vs. Ho-listic	Instinctual vs. Not
I rely on my first impressions.	0.086	0.208	0.654
I am detail oriented and start with the details in order to build a complete picture.	-0.711	-0.066	-0.057
I find that to adopt a careful, analytic approach to making decisions takes too long.	-0.005	0.699	0.166
I go by what feels good to me.	-0.055	0.289	0.680
When making a decision, I take my time and thoroughly consider all relevant factors.	-0.794	-0.098	0.067
I do not like detailed explanations.	0.220	0.570	0.173
I reason things out carefully.	-0.748	-0.139	0.000
Given enough time, I would consider every situation from all angles.	-0.747	-0.034	0.061
I do not tackle tasks systematically.	0.058	0.753	0.047
I use my instincts.	-0.100	-0.033	0.798
I do not approach tasks analytically.	0.108	0.759	0.103

A2.2. Cognitive-Style Factor Loadings for Automotive Three-Phase Experiment

	Rational vs. Intuitive	Impulsive vs. Deliberative	Ignore Images, Focus on Details
I reasoned things out carefully.	0.71	-0.32	0.01
I tackled this task systematically.	0.58	-0.37	0.15
I figured things out logically.	0.64	-0.33	0.18
I approached this task analytically.	0.62	-0.40	0.16
I applied precise rules to deduce the answer.	0.63	-0.18	0.16
I was very aware of my thinking process.	0.62	-0.24	0.04
I used my gut feelings.	0.29	0.72	0.08
I went by what felt good to me.	0.30	0.69	0.13
I relied on my sense of intuition.	0.41	0.67	0.06
I relied on my first impressions.	0.22	0.66	0.14
I used my instincts.	0.30	0.67	0.11
Ideas just popped into my head.	0.30	0.59	0.05
I tried to visualize the images as 3-D shapes.	0.54	0.24	-0.26
I read the text carefully.	0.57	-0.25	-0.13
I skimmed the text.	-0.18	0.23	0.31
I concentrated on the images.	0.48	0.44	-0.34
I ignored the images.	-0.20	-0.15	0.66
I made comparisons of different facts.	0.53	-0.16	-0.09
I made comparisons between different images.	0.47	0.19	-0.27
I did not notice there were video reviews.	-0.22	0.05	0.58
The video reviews were helpful in making my decision.	0.49	0.29	-0.19
I like detailed explanations.	0.53	-0.21	0.02
I enjoy deciphering graphs, charts and diagrams about products and services.	0.56	-0.19	0.12
I prefer planning before acting.	0.49	-0.31	0.06
I'm usually more interested in parts and details than in the whole.	0.31	0.23	0.43
I like to make purchases without thinking too much about the consequences.	0.11	0.47	0.31
I tend to see problems in their entirety.	0.52	-0.18	0.08
I see what I read in mental pictures.	0.55	0.20	-0.13
I am detail oriented and start with the details in order to build a complete picture.	0.60	-0.23	0.17

Appendix 3 Estimation of $\vec{\omega}_r$ for the CNET Experiment

We follow the procedures detailed in HULB to estimate click-characteristics preferences, which were used in the CNET experiment to compute the posterior estimates of cognitive styles in real-time. Table A3.1 shows the maximum likelihood estimates of $\vec{\omega}_r$. This estimation explains 60.5% of the uncertainty (U^2 [pseudo-R^2] of 0.605).

Table A3.1. Maximum-Likelihood Estimates of $\vec{\omega}_r$ for CNET Experiment

	Constant	Impulsive vs. Deliberative	Analytic vs. Holistic
Expect the linked page to have pictures or graphs	0.257 [a]	0.209	-0.292 [a]
Expect the linked page to be focused on a specific question (technical)	-3.947 [a]	-1.120 [a]	1.351 [a]
Expect the linked page to have large amount of data	1.181 [a]	0.095	-0.221
Navigation Bar	6.931 [a]	-2.459 [a]	2.349 [a]
Carousel	3.946 [a]	0.190	0.665 [b]
More Stories	5.208 [a]	1.053 [a]	0.808 [a]
Promotion Bar	5.762 [a]	-1.853	2.630 [b]
Popular Topics	3.818 [a]	1.517 [a]	-0.981 [a]
Tabs	-14.585	1.236	-0.032
Inside CNET	5.036 [a]	2.597 [a]	-0.858 [b]
Search category	3.706 [a]	-2.856 [a]	2.818 [a]
Product-specific reviews	3.741 [a]	-2.299 [a]	2.083 [b]
Social Influences: expert opinion ("CNET says")	3.360 [a]	1.322 [a]	-1.226 [a]
Social Influences: consumer opinion("what other do")	2.087 [a]	0.768 [a]	-0.237
Tech-savvy	0.263 [b]	0.036	-0.176

[a] Significant at the 0.05 level. [b] Significant at the 0.10 level.