**What Voters Do:**
**Information Search during Election Campaigns**

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## Abstract

Learning about political candidates in order to vote can be a cognitively taxing task, given that the information environment of a campaign may be chaotic and complicated. In order to tame the tide of information voters may adopt decision strategies that guide their processing of campaign information. This paper reports results from a series of process tracing experiments designed to learn how voters in a presidential primary election adopt and use such strategies. Different voters adopt different strategies with the choice of strategy dependent on the campaign environment and individual voter characteristics. The adoption of particular strategies can have implications for how voters evaluate candidates.

Keywords: Information Search, Decision Making, Process Tracing, Voting

## What Voters Do:
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In order to cast a meaningful vote, voters presumably must learn something about the candidates. Normatively, more information is thought to be better than less; voters should have an extensive store of knowledge arrived at through comprehensive information search that considers all candidates on all attributes. Of course, most citizens do not actually do this, and this failure to learn very much is usually considered an impediment to good citizenship. Yet, to expect citizens to readily engage in extensive search flies in the face of known information processing limits. Variously called “cognitive misers” (Taylor, 1981) or “boundedly rational” (Simon, 1957), humans simply can not operate as purely rational calculators (Redlawsk, 2002.) But, as Simon (1956) pointed out, they may not have to. Using various shortcuts, or heuristics, voters may be able to make good decisions even without learning all there is about the candidates (Lau & Redlawsk, 2001a.) Sometimes good enough can be good enough.

Despite the evidence that voters have little information at the ready, some political learning does in fact take place during campaigns and voters use their knowledge, however little, to inform their decisions (Markus & Converse, 1979.) Learning takes place in an often chaotic environment where information flows at an overwhelming pace. To tame this tide, voters can adopt information search and acquisition strategies based on both their own abilities and the complexity of the particular political environment. These strategies, some of which lead to limiting information search, are likely to have implications for how voters learn about and evaluate candidates. But while there has been debate over how much learning occurs, there has been little work directly examining how voters acquire information in the first place.

This paper reports on experiments examining how voters search for and acquire information during a campaign. Information search patterns can be identified which in turn define the decision rules voters use to make sense of the campaign environment. Through the use of a "dynamic process tracing" technique that tracks information search and acquisition as it happens (Lau, 1995; Lau & Redlawsk, 2001b; Lau & Redlawsk, 1997), voters are presented with campaigns modeled on a real-world political environment. The type and amount of information acquired by voters can be tracked as it happens allowing direct examination of the question "What do voters do when they are learning about candidates?"

## Theoretical Background

Behavioral Decision Theory (BDT) provides theoretical guidance for this paper and for the dynamic process tracing methodology. In contrast to the normative focus of rational choice, BDT takes as its primary goal the understanding of how people actually make decisions (Payne, Bettman, & Johnson, 1993.) No study of decision making has ever shown people actually processing information according to the all-knowing omniscience that seems to be required of most normative models. Instead, people often settle for "good enough" once they learn an adequate amount about the choices they face. Value maximizing behavior simply does not occur in complicated decision environments (c.f. Dawes, 1988).

However, decision makers generally want to do a good job and thus may develop strategies to overcome cognitive limits (Payne, Bettman, & Johnson, 1993.) But these strategies can result in failure to make normatively correct decisions because decision makers often face competing goals: to make good decisions, but to use the minimum necessary cognitive resources to do so (Stroh, 1995; Lau, 2003.) For some decisions the competition between these goals is minimal. Perhaps the alternatives are few, the number of attributes limited, and the decision relatively unimportant. Making an accurate decision under such circumstances may not be taxing. But when alternatives are many or indistinct, when information is overwhelming, and the decision important, decision makers may run up against their cognitive limits.

In any case, the search for information and its integration takes cognitive effort. Much of that effort goes into comparing alternatives on a range of attributes (Rahn, 1995). People may generally adopt one of two sets of comparison rules (Payne, Bettman, & Johnson, 1993.) With *compensatory* rules, the different attributes of an alternative are explicitly compared to one another on some commensurate scale (like the economists' "utility"), so that a low score on one attribute can be traded off or compensated for by a high score on another (Lau, 1995). This process is cognitively taxing, easily creating value conflict if one alternative is preferred on one attribute while another is preferred on a different attribute (Ford, Schmitt, Schechtman, Hults, & Doherty, 1989.) The difficulty increases when the trade-off is between incommensurate attributes, such as the apples and oranges comparison of a stand on abortion *versus* the Israeli-Palestinian conflict. Preferring one candidate on one of these may have to be balanced against preferring another candidate on the other. How to make the trade-off? The "rational" answer is to compute the utility of each attribute for each candidate and then summarize into an overall utility for each candidate. Once this is done, the decision maker "simply" chooses the candidate who maximizes utility. These calculations are cognitively difficult, and thus in many cases may be abandoned for an alternative approach.

The alternative is a *non-compensatory* rule. Generally speaking, people try to avoid making the value trade-offs typically required by compensatory rules (Lau, 1995; Hogarth, 1987). Rather than make direct comparisons on multiple attributes voters may simply use a rule that considers alternatives serially, one attribute at a time. Alternatives that do not meet a minimum expectation level on an attribute are immediately discarded, thus eliminating tradeoffs. The decision rule may well entail simply choosing the first candidate who meets the minimum requirements on the most important attributes. Non-compensatory rules are clearly less taxing because they rely on incomplete search (Lau, 2003.) Instead of making trade-offs, a decision maker simplifies the environment by dropping alternatives as soon as possible. Yet in doing so, important information about some alternatives may never be examined and thus never considered in the decision calculus. It is certainly possible that a candidate who fails to meet one requirement may yet be the best alternative on every other requirement. Thus the use of a non-compensatory rule may easily result in failure to choose the utility maximizing alternative.

Why should we care about what rules voters use to acquire information; whether they make value tradeoffs or simply limit search? The process may be conscious; that is a voter may decide ahead of time to focus on only one candidate, or on a limited set of issues. Or it may be that the information environment becomes so rich – think nine Democratic candidates in the 2004 Iowa Caucuses – that full information search is not possible, no matter how conscientious the voter. In either case the strictures of a "rational" decision making process are not going to be met. If information search varies in systematic ways then it becomes important to understand the conditions under which it does so since decisions made with limited information may be different from those made more by more fully informed voters (Lau & Redlawsk, 1997.) Thus it is important to understand how and when voters actually adopt specific decision rules.

## Information Search and Decision Rules

The decision rules employed by voters can be determined by examining the information search undertaken during a campaign. Particular information search patterns imply specific decision rules and can be identified by three key search process measures (Lau, 1995; 2003.) The first, *depth of search*, refers to the amount of available relevant information actually considered in making a decision. Search can be deep, examining nearly all attributes available for every relevant candidate. Or, the focus may be on a limited set of attributes, and/or a limited set of candidates. Deep search suggests a compensatory rule while shallow search suggests little effort to compare candidates and few tradeoffs; the hallmarks of non-compensatory rules.

Next is the *comparability of alternatives* under consideration, indicating the extent to which a voter gathers the same information about all relevant candidates. High inter-candidate comparability suggests that consideration of each candidate is roughly equal. When combined with a deep search, this provides further evidence of a compensatory rule. Alternatively, low inter-candidate comparability occurs when information acquisition varies substantially between candidates and suggests the use of a non-compensatory rule, especially with shallow search.[1]

Finally, *sequence of search* – the order in which information is accessed –also provides insight into decision rules. Voters may access information randomly, or they may use one of two systematic approaches. The first, *intra-attribute* search, describes making transitions from an attribute for one candidate to the same attribute for another candidate. The second pattern is *intra-candidate*, where voters search within a single candidate to learn multiple attributes before switching to another candidate. This focus on transitions is a particular strength of information board methodologies (Jacoby, Chestnut, Weigl, & Fischer, 1976.) All decision rules suggest voters should employ one or the other of the two systematic search sequences.[2]

Taken together, these measures can be used to identify specific decision strategy. Adoption of a strategy is a function of the decision environment – for example, the number of alternatives – and the cognitive abilities of the decision maker.[3] Given that normative models argue that voters should have a great deal of information about all alternatives, the choice of search strategy, and the decision rule implied thereby, clearly has implications for the ability of a voter to meet normative expectations.

## Process Tracing

Information search studies generally use laboratory-based process tracing techniques to track decision making. The most common technique is the static information board, presenting subjects with a matrix of information arranged so that accessing information about alternatives (candidates, in this case) is done by clicking on a box on the computer screen.[4] The participant learns about candidates and issues by choosing them in any sequence desired; thus search is completely controllable. Information is always available and easy to access. This static board models a nearly *ideal world* environment. But the real political world is not static, and such studies do not give a very good feeling for what happens in the relative chaos of a real election.

A new process tracing technique, the *dynamic information board* (Lau, 1995; Lau & Redlawsk, 1997, 2001a, 2001b; Redlawsk, 2001, 2002), radically revises the static technique to better model campaigns, creating a more complicated environment where information flows over time, coming and going as the campaign progresses. In choosing to examine one piece of information a voter may forgo the opportunity to learn something else since the available information is always changing. Like the static board, attribute labels include a candidate's name and the information to be revealed if the label is accessed. But unlike the static board, only a small subset of a very large database is available at any one time, making the task of processing the campaign much less manageable. The relative likelihood of any piece of information becoming available is controlled, so that some information (like party identification) appears much more often than other information (such as an obscure policy position.) This design creates a closer analog to a *real world* campaign compared to the traditional static board.

## Hypotheses

The information board frameworks, both static and dynamic, provide a platform for examining information search and acquisition during political campaigns. It is certainly possible that search is essentially random, driven by the order in which information is available rather than by the adoption of any particular strategy. Alternatively, voters may adopt a structured search strategy – whether compensatory or non-compensatory – in an effort (which may not be successful) to best make sense of things. Whether search is something other than random is may be a factor of the information environment itself. When information is easily managed, a structured strategy may not be needed. Thus Hypothesis 1:

> $H_1$: *In a more difficult decision environment, information search will be more structured as evidenced by a greater likelihood that voters will use an identifiable decision rule.*

Since decision makers are motivated to make good decisions with minimal effort (Lau, 2003), the type of decision rule used should be a function of the difficulty of the decision task and the expertise of the decision maker. Compensatory rules require careful attention to a wide range of information, while non-compensatory rules are far less cognitively taxing. Thus if a particular decision involves relatively few alternatives differing on only a handful of attributes, decision makers should be more likely to employ a compensatory rule. Similarly, a person with greater cognitive resources may be better positioned to employ a compensatory rule compared to a person operating with little prior knowledge or experience. Hence:

> $H_2$: *Compensatory decision rules are more likely to be used in the easiest decision environments, while non-compensatory rules will predominate in more complex environments. Those with greater cognitive resources will be more likely to employ compensatory rules.*

Are there consequences associated with the adoption of certain decision rules? Clearly, different search strategies will result in different levels of knowledge about the available candidates. These differences may in turn affect candidate evaluation. In particular, voters using a compensatory rule and learning a lot about multiple candidates could be expected to moderate their evaluation of the preferred candidate since they are likely to learn things they like about otherwise rejected candidates. In searching more deeply voters are also likely to learn a greater mix of good *and* bad about the candidate they prefer. Conversely, voters focused mostly only one candidate and learning little about the others may rate their preferred candidate more highly. After all there would be little comparison to other candidates, and therefore less countervailing information to depress the evaluation of the vote choice. This leads to Hypothesis 3:

> $H_3$: *Voters using compensatory rules will give their chosen candidate a lower global evaluation than those using non-compensatory rules, while giving rejected candidates higher evaluations. Overall, the use of compensatory rules should moderate candidate evaluations relative to those reached by voters employing non-compensatory rules.*

## Data and Method

### The Process Tracing Studies

Data were collected through a series of process tracing experiments, most of which used the dynamic information board, with one using a static board. The experiments have been described in detail elsewhere (Lau, 1995; Lau & Redlawsk, 1997) and will only be briefly described here. The total subject pool is a non-probability sample of 656 adult citizens, 599 using the dynamic board and 57 using the static, recruited in central New Jersey between 1994 and 1997. All subjects were eligible U.S. voters, although they did not have to be registered to vote. Subjects could not be attending college. The studies began with the completion of a political attitudes questionnaire. Subjects then participated in a simulated presidential primary election, and in most studies, in a general election campaign.[5] The candidates, while fictitious, represented a realistic spectrum of ideologies across both major political parties. Before the primary, subjects "registered" with a party, and were subsequently constrained to vote only for candidates from that party in the primary, although information about candidates from both parties was always available. After completing the primary (which lasted about 22 minutes) subjects voted and then rated all candidates on a 101-point feeling thermometer. Next they answered questions about the difficulty of their decision and for all but one study, learned which candidates were running in the general election and began that election. Following the general election campaign, subjects again voted, evaluated candidates, and answered questions about their decision. Next, an unexpected memory test was given about the general election. Subjects were then debriefed, paid, and dismissed. This paper focuses on the primary campaigns only.[6]

Each experiment involved several manipulations. Of theoretical interest here is the manipulation of the number of candidates available in the voter's party during the primary election. Subjects were randomly placed into one of two conditions, with either two ideologically distinct candidates in their party, or four candidates arrayed along their party's ideological spectrum. This latter condition should be significantly more difficult. In addition, in one study the information board itself was manipulated, so that some subjects worked on a static board while others used the dynamic board. This manipulation also varies the difficulty of the task, with the static board presenting the more manageable "ideal world" environment.

**Key Measures**

Of the three measures of information search described earlier, two are used to determine whether compensatory or non-compensatory rules were employed. The third, sequence of search, can be used to further differentiate the specific rule within these types, but such fine grained analysis is not the purpose of this paper.

Depth of Search. Depth is computed as the mean of two search measures: the number of non-redundant attributes and the number of distinct pieces of information examined for all relevant (i.e., in-party) candidates. The first component includes only the unique attributes considered, regardless of how many times the same attribute was considered for different candidates. The second component is the total number of unique, non-redundant attributes accessed across all in-party candidates.[7] These two measures were standardized and averaged to create a Depth of Search score computed on a 0-100 scale. A high score indicates deep search.

Comparability of Search. While the depth measure indicates how much relevant information was accessed, it does not tell us anything about comparisons voters might make between candidates. The standard measure of comparability is the variance in the number of unique items accessed per alternative (Payne, Bettman, & Johnson, 1993.) Greater variance indicates a search focused more on one alternative while lower variance indicates a more balanced search. However, this standard measure actually fails to indicate how directly candidates were compared. It is clearly possible to learn ten things about one candidate and ten *different* things about a second candidate, resulting low variance but no true comparative search. A more accurate measure is to consider the proportion of all distinct attributes considered, that were examined for all candidates in the choice set. The higher this proportion, the more the same attributes were examined across multiple candidates. This score was also scaled from 0-100.

While these two measures give specific information about how subjects searched for information they cannot be directly compared across the static and dynamic information boards. Measures for the dynamic board subjects are computed separately from those for static board subjects and the standardization of the variables is within information board type. This was done because the very nature of the boards is so different as to not be directly comparable. Even so, the measures can be used to determine the search strategies for each board, and the resulting decision rules can be compared between the two types of information boards.

## What do Voters do?

Table I describes the key search measures based on the number of candidates in the primary election for both the static and dynamic information board environments, along with the total information viewed for all candidates. Subjects in the static information board looked at only about half as much information as those using the dynamic board but within each type of information board there is no difference in overall information search between the two and four candidates condition. Turning to the search measures, in the static environment there is no difference in depth of search based on the number of candidates. But there is some difference in the comparability of search, as subjects facing only two candidates in their party tended to search for comparable information across the candidates more than those facing four candidates ($t=2.068$, $p<.05$). Such results would be expected if those in the more difficult four candidate condition limited their search to fewer than the full set of candidates. A similar pattern exists for comparability in the dynamic board, where again there is greater comparability in the easier two candidate condition ($t=13.229$, $p<.01$). But while these subjects engage in more comparable search, they search less deeply than those in the four candidate dynamic condition ($t=-2.679$, $p<.01$). Facing fewer candidates makes direct comparison easier while less information is needed to differentiate between preferred and non-preferred options. Thus there is initial evidence that the decision environment has noticeable effects on search strategies.

[Insert Table I about here]

No standard exists for how deep or comparable search must be to be “rational”. While these measures do indicate the specific decision rule pursued (Lau, 2003; Payne, Bettman, & Johnson, 1993) the actual cut points are arbitrary. For this analysis the search measures are each stratified at the median in order to place subjects into compensatory, non-compensatory, or non-structured search. The process is an “anding” one; for example, to be placed into the compensatory rule, a subject must evidence greater depth AND higher comparability, while the non-compensatory rule requires shallower search AND lower comparability. With two dichotomous dimensions, there are of course 2 x 2 = 4 different possibilities. However, only two have been identified in the BDT literature as structured strategies. The other two (deep search of limited comparability and shallow search of high comparability) are considered unstructured search (see Footnote 1). Overall, a structured strategy can be identified for just over 50% (29) of subjects in the static condition and 66.8% (400) in the dynamic information board condition.

Hypotheses 1 and 2 suggest conditions under which information search strategies may be employed. Hypothesis 1 suggests that voters in complicated decision environments are more likely to adopt a structured search strategy compared to those facing simpler decisions. This is easily tested by examining the cross-tabulation between structured search and the two manipulations of difficulty; the static/dynamic and the two/four candidate manipulations. As Table II shows, and as expected, structured search is greater in the dynamic environment's two candidate condition, compared to the static environment (73.6% vs. 41.4%; $X^2_1$=12.714, $p$<.01, one-tailed) Yet the pattern does not hold for the four candidate condition, where no significant difference exists (55.4% vs. 60.7%; $X^2_1$=.283, n.s.) Turning to results within each information board environment, the findings are again mixed. In the static environment there is more structured search in the four candidate condition (60.7% vs. 41.4%; $X^2_1$=2.131, $p$<.1, one-tailed). But in the dynamic environment, the number of candidates has the opposite effect from as those in the more difficult four candidate condition are *less* likely to engage in structured search (55.4% vs. 73.6%; $X^2_1$=18.077, $p$<.01, one tailed). Support for Hypothesis 1 is mixed at best.

[Insert Table II Here]

Hypothesis 2 considers the conditions under which compensatory or non-compensatory rules are employed. Since compensatory rules are cognitively taxing they should be employed when the environment is easily managed or when sufficient cognitive resources and motivation to make the necessary comparisons exist. On the other hand, when the environment is complex, the use of a simplifying non-compensatory rule should be more likely. Table II provides some evidence in support of this – in both the static and dynamic environments subjects facing four candidates were more likely to use a non-compensatory rule. In addition, subjects in the more demanding dynamic environment appear less likely to use a compensatory rule than those in the easily managed static environment. To explore this further a logistic regression model predicting use of a compensatory rule was developed. The model includes the static/dynamic environment and the number of candidates as indicators of difficulty. Individual cognitive capacity is measured by age and education, while political expertise is included to test for domain specific knowledge. The results are presented in Table III. The model is reasonably strong, correctly classifying more than 76% of cases. Supporting Hypothesis 2, both measures of the difficulty of the information environment are in the expected direction though only the two/four candidate manipulation is significant. The small number of cases (29) in the static condition probably has some effect here. But in general when the information environment is more difficult voters adopt a simplifying search strategy. Interestingly, political expertise has no effect; experts are no more likely than non-experts to use a compensatory strategy. But both age and education are significant. Older people are less likely to use compensatory strategies, which makes sense given the tendency for cognitive function to decrease with age (Riggle & Johnson, 1996.) Education also predicts the use of compensatory search, with better educated voters making greater use of such search under all conditions.[8]

[Insert Table III Here]

Hypothesis 3 argues that the employment of a particular information search strategy has politically relevant effects. Voters who use a compensatory rule should rate their preferred candidate somewhat lower and rejected candidates somewhat higher than those who use a non-compensatory rule. Two Repeated Measures ANOVA models were constructed with the feeling thermometer for the chosen candidate and the mean feeling thermometer for all rejected candidates as the dependent variables.[9] One model tested the dynamic information board condition while the other the static information board. Entered into the models were the type of decision rule employed, the number of candidates manipulation, subject expertise, and to adjust for differences in the use of the feeling thermometer scale (Brady, 1985), the mean FT rating for all (real) politicians evaluated in the initial political attitudes questionnaire. Political expertise is used, rather than education, because the specific task is rating candidates, which should implicate the components of expertise (political knowledge, interest, involvement.)[10]

The resulting models show support for the hypothesis. The expected pattern is found in the static environment, as subjects using a compensatory decision rule rate their preferred candidate lower and rejected candidates higher. However, the small number of cases again means that the difference does not reach statistical significance. In the dynamic environment, significant effects for decision rules on candidate evaluation are found ($F=8.770$, $p<.01$) but the effects are limited to rejected candidates. As Figure 1 shows the rule employed makes no difference in evaluation of the preferred candidate. However, in evaluating rejected candidates, subjects using a compensatory rule rate them over 6 points higher (on the 101 point scale) than those using non-compensatory rules ($b=6.099$, $t=-10.231$, $p<.001$.) Taken together, these results support the notion that as voters learn more about candidates, they may find more to like about their less preferred options. Those who choose to focus mostly on their preferred candidate never learn much to like about other choices. But as they learn more about their preferred choice, they either do not learn disliked information or they fail to take into account negatives they do learn.[11]

[Insert Figure 1 about here]

## Discussion

This paper examines the role information search and acquisition plays in voter decision making. Two different process tracing methodologies were used to capture information search as it occurred. Using these two different approaches allows the decision process to be examined in both a more "perfect world" where information is easily obtainable and in a more "real world" analog where information flows in a chaotic and uncontrollable manner. The resulting process information makes visible the search strategies voters use and the rules theses strategies infer.

What is found is instructive. First, identifiable decision rules can indeed be seen in most subjects, especially in the more realistic dynamic campaign environment. Some people appear to follow the normative prescription that all (most) attributes for all candidates should be examined to make the best decision. Compensatory rules are particularly evident when the information environment is relatively simple and the decision is relatively easy. On the other hand when the environment is complicated, search strategies often adjust as voters use non-compensatory rules to make sense of the world by simplifying it. These simplifying strategies have implications for candidate evaluation. Those engaged in deep, highly comparable information search may find that they learn things they do not like about their preferred candidate and things they do like about others. Learning such information may make the decision environment even more difficult to manage. It certainly is easier to just assume that one will like a preferred candidate's position on all issues without bothering to look. But when voters do look at other options, they revise their evaluations accordingly, which in some circumstances may well increase ambivalence, as evaluations between preferred and less preferred candidates become less distinct.

Studying information search and acquisition may seem somewhat esoteric. Yet ultimately campaigns are about information, as candidates try to get voters to pay attention and learn something. How voters actually go about "learning something" is of significant importance to the decisions they make in the voting booth. All political science models of the vote assume the acquisition of information, but none specify how variations in information acquisition might well implicate the vote itself. As a first step this paper has shown that there are, indeed, variations in how voters acquire information and more importantly, that those differences are a function of both the way in which information is structured (Rahn, 1995) and the complexity of the decision task. Only when the task is simple do voters come close to the normative rational prescription of full information search. But in what would seem to be a more realistic campaign environment, simplifying non-compensatory rules come to the fore, and voters do not learn the same amount of information about all candidates. Many years ago Simon (1956, 1957) argued that the use of simplifying strategies, while not optimizing, result in decisions that are good enough most of the time. The question remaining is whether the same is true for voters who fail to learn everything about everyone – which is of course most voters. It is clear that information search matters, but more research is needed to establish exactly how information learned becomes a decision made.

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**Table I**
**Search Strategy Components**

| # of Candidates: | Static Environment Two | Four | | Dynamic Environment Two | Four | |
|---|---|---|---|---|---|---|
| Total Number of Items Examined | 35.00 (15.69) n=29 | 30.96 (18.36) n=28 | t=1.070 | 74.56 (27.81) n=395 | 72.08 (25.02) n=204 | t=.893 |
| Depth of Search | 49.00 (21.95) n=29 | 46.40 (27.70) n=28 | t=.633 | 46.83 (19.19) n=395 | 50.39 (17.95) n=204 | t=-2.198** |
| Comparabilty of Search | 56.47 (35.77) n=28 | 38.96 (26.99) n=28 | t=2.068** | 57.93 (13.72) n=392 | 42.85 (12.07) n=203 | t=13.229*** |

Table entries are means, standard deviations are in parentheses. Scale for measures is 0 – 100.
*$p$<.10, **$p$<.05, ***$p$<.01

**Table II**
**Structured Information Search**

| Search Type | Static Environment Two Candidates | Static Environment Four Candidates | Dynamic Environment Two Candidates | Dynamic Environment Four Candidates |
|---|---|---|---|---|
| Structured Search | 41.4% (12) | 60.7% (17) | 73.6% (287) | 55.4% (113) |
| Compensatory | 27.6% (8) | 25.0% (7) | 42.8% (167) | 16.7% (34) |
| Noncompensatory | 13.8% (4) | 35.7% (10) | 30.8% (120) | 38.7% (79) |
| Unstructured Search | 58.6% (17) | 39.3% (11) | 27.3% (108) | 44.6% (91) |
| | n=29 | n=28 | n=390 | n=204 |

Structured vs. Unstructured Search one-tailed tests:

Static Two Candidate vs. Dynamic Two Candidate: $X^2_1=12.714$, $p<.01$
Static Four Candidate vs. Dynamic Four Candidate: $X^2_1=.283$, n.s.
Within Static Environment: $X^2_1=2.131$, $p<.10$.
Within Dynamic Environment: $X^2_1=18.077$, $p<.01$

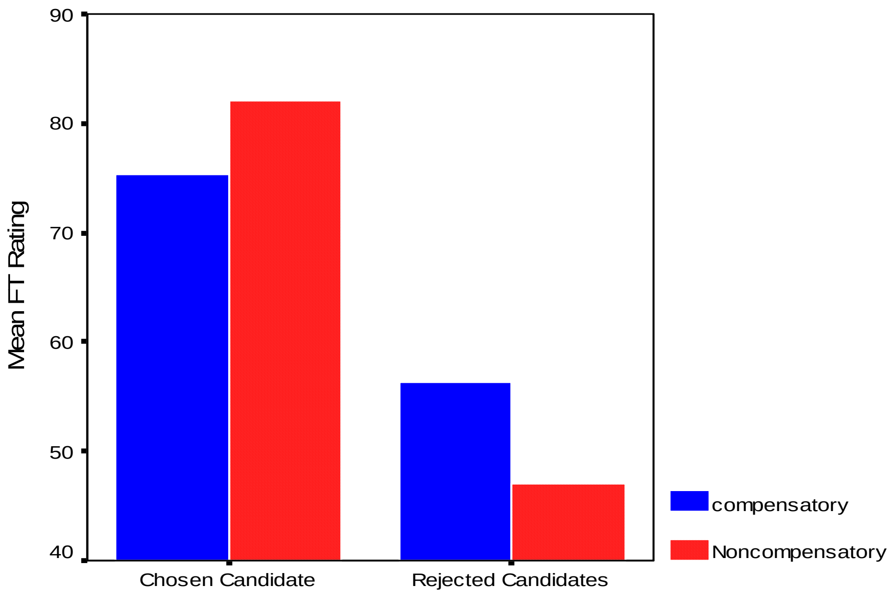
**Table III**
**Factors Influencing the Use of Compensatory Search**

| | |
|---|---|
| Election Characteristics | |
| Number of Candidates | -1.370*** |
| (1=Four) | (.302) |
| Information Board | -.407 |
| (1=Dynamic) | (.542) |
| Voter Characteristics | |
| Political Expertise | .225 |
| (1=expert) | (.262) |
| Education | .343*** |
| | (.084) |
| Age in Years | -.056*** |
| | (.008) |

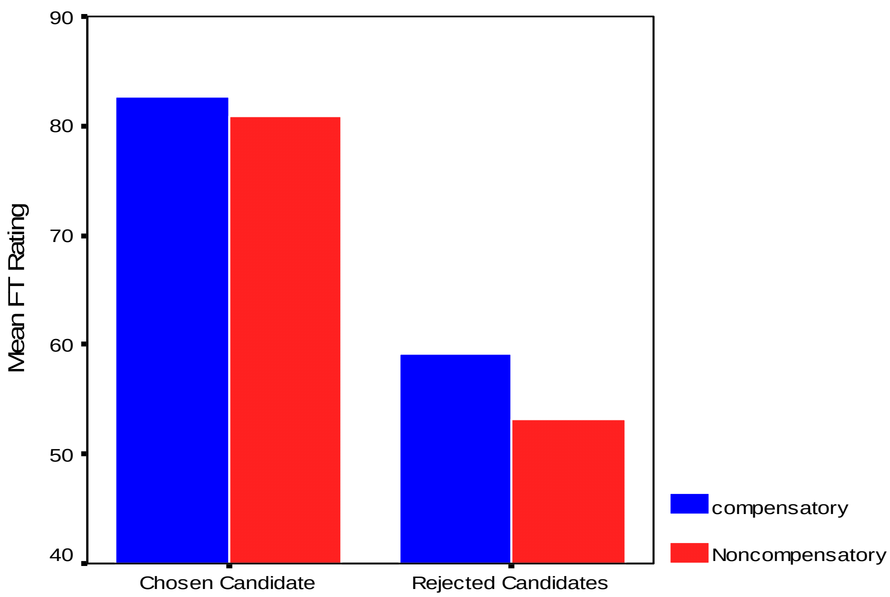
Table entries are logistic regression coefficients. Dependent Variable coded 1=compensatory search. Model includes dummy variables to control for each separate experiment and a constant, not shown. n=421, $X^2_9$=157.187 ($p$<.001); pseudo-$r^2$=.312.
*p<.10 **p<.05 ***p<.01

**Figure 1**
**Effects of Decision Rules on Candidate Evaluation**

**Static Information Board**




**Dynamic Information Board**

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For static information board, n=26; for dynamic information board, n=350.
Differences in static information board are not statistically significant (chosen, t= .615, n.s.; rejected, t=-1.263, n.s.) Differences in dynamic information board are significant for rejected candidates (t=-10.231, $p$<.001), and not significant for chosen candidate (t=-1.106, n.s.)

**Footnotes**

1. It is possible for shallow search to be highly comparable; a voter might examine all candidates on only one or two issues. This is indicative of single (or limited) issue voting more than anything. Alternatively, one could focus exclusively on a single candidate and learn much about that candidate, showing deep search but little comparability. Even so, by definition such search could not be as deep as search that includes multiple candidates since there is only so much information available about each candidate. Analyses here will exclude these non-standard strategies.

2. One can make a transition from viewing one candidate on an attribute to viewing another candidate on a different attribute. Such search is not systematic, making comparisons neither along candidate nor attribute dimensions.

3. Rahn (1995) looks at how campaign information is organized in memory and finds that the propensity is to organize it by attribute, except when the information is specifically presented in a candidate-salient display. Thus the search sequence appears to directly relate to the way in which information is organized in memory.

4. There are relatively few examples of the use of a static information board to study candidate evaluation and voting. Herstein's (1981) study was the first; more recently Rahn (1995), Riggle & Johnson (1996), Mintz, et al. (1997), Huang (2000), and Huang & Price (2001) have all reported studies using some variant of this technique.

5. See Lau & Redlawsk (1997, Fig. 2, 588) for a convenient summary of the typical procedure.

6. The dataset merges data from four experiments. Clearly variation from one experiment to another may influence the adoption of different strategies. In addition to a "number of candidates" manipulation discussed below, the experiments included manipulations of campaign advertising tone, the amount of campaign resources, and variations in candidate ideologies. To control for these effects dummy variables are used indicating the experiment in all multivariate analyses, though the coefficients are not reported here. The full models are available from the author.

7. Subjects in the four candidate condition examined more in-party information than those facing two candidates, a reasonable response to the presence of more candidates (two=41.8; four=65.9, t=12.204, $p<.001$.) Given four candidates and limited time, the mean number of attributes examined per candidate should be lower in the four candidate condition, as it is (two candidates= 20.5; four candidates = 16.5, t=5.820, $p<.001$.) Adjusting for the number of candidates would obscure the tendency of subjects with four candidates to spend more time focused on in-party candidates, an important response to the more complicated environment, so no adjustment is made.

8. Interaction terms for both education and expertise with the difficulty manipulations were included in an initial model, but were neither significant nor substantial, and were dropped from the final model.

9. In the 2-candidate condition there is only one rejected candidate, and that candidate's feeling thermometer is used. In the 4-candidate condition there are three rejected candidates, however, so the mean of those three individual evaluations is taken to represent evaluation of the rejected candidates.

10. Education was initially entered into the analysis, along with age and gender. No effects were found for any of these controls and they were dropped.

11. Recent research on the role of affect in decision making (Redlawsk, 2002; Lodge & Taber, 2000 may support this latter possibility. Studies find that encountering negative information about a liked alternative may result in an increased preference for the alternative; new negative information may not generate accurate preference updating.