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Choice-Based Conjoint Study of Recruitment Incentives

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EXECUTIVE SUMMARY

INTRODUCTION

As the Navy continues to face a significant challenge in meeting its recruiting goals, Commander, Navy Recruiting Command (CNRC) is interested in finding new and innovative incentive packages to attract greater numbers of high-quality accessions. In this study, CNRC tasked CNA to explore three questions:

- Which attributes of an enlistment package do potential recruits consider most important?
- What are the tradeoffs among various elements of a possible enlistment package?
- What elements of an enlistment package are most likely to help the Navy in its efforts to expand beyond its traditional recruiting base?

There are at least two possible approaches to answering these questions. The first is an econometric approach using historical data on actual enlistments, and the second is an operational market research approach using stated-preference data. Although both approaches are necessary to provide a complete picture of the recruiting market, we used the market research approach because it provided two distinct advantages over the historical data approach: First, CNRC wants to know how to use larger financial incentives and new non-financial incentives to expand its share of the employment market. Analysis of these new programs cannot be done using historical data. Second, the market research approach allowed us to collect information on young people who have not yet made an enlistment decision.

The second point is particularly important. If the Navy is to expand its recruiting market, it must offer enlistment packages that appeal to those who have some interest in military service but are not currently choosing to enlist. We describe this group as having a "medium propensity" to enlist. This group—in contrast to either the "high-propensity" group or the "no-propensity" group—is critical for improving recruiting results, and is therefore the focus of this analysis. If we can better understand the preferences of the medium-propensity group, we can help the Navy design enlistment packages to induce this group to join.

FINDINGS

We analyzed the relationship between enlistment propensity and recruitment incentives using two approaches. First, we divided the sample into three groups—high-propensity, medium-propensity, and no-propensity—and showed that preferences differed by propensity group. Second, for the whole sample, we measured the impact of changes in different components of a hypothetical enlistment package on the likelihood of indicating a willingness to join the Navy . The second approach allowed us to make direct estimates of the impact of different policy options on enlistment propensity.

Results of these analyses reveal valuable insight into young people's preferences for the different attributes of an enlistment package. Combined with demographic data, the self-reported enlistment propensities and the preference data also give some indications about how the different attributes of the enlistment package can be used to attract different kinds of recruits. The primary results are listed below.

Determinants of Propensity:

- Relative to high-propensity respondents, medium-propensity respondents do better in high school and are more likely to be planning on pursuing post-secondary education before entering the labor force. Thus, when they reach the labor market, members of the medium-propensity group will likely have more—and more lucrative—opportunities in the civilian sector than will their higher-propensity counterparts.

Importance of Each Attribute:

- Length of obligation is more important for medium-propensity respondents than for high-propensity respondents.

- College-related incentives are more important for medium-propensity respondents than for high-propensity respondents.

- Navy job is more important for high-propensity respondents than for medium-propensity respondents.

Enlistment bonus (EB) vs. Navy College Fund (NCF):

- Medium-propensity respondents have stronger relative preferences for NCF than do high-propensity respondents. Therefore, offering NCF is a more cost-effective way of expanding the recruiting pool than offering EB.

Trade-offs Between EB and Non-Financial Incentives for Medium-Propensity Respondents:

- Length of obligation:
    - In terms of EB, the cost per year of a five-year commitment is 1.6 times that of a four-year commitment.
    - In terms of EB, the cost per year of a six-year commitment is 2.7 times that of a four-year commitment.

- College credit:
    - The EB equivalent value of one or two semesters is about $2,000 per semester.
    - The EB equivalent value of a third or fourth semester is about $5,000 per semester.

- Navy job:
  - Rating-specific bonuses can be used to steer recruits into critical ratings. This is already being done.

Enlistment Propensities for the Whole Sample:

- Offering appropriate amounts of college credits for Navy training in different programs has a large positive effect on propensity—approximately 3 percentage points.

- Increasing obligation lengths by just one year has a substantial negative effect on propensity—approximately 2 percentage points.

CONCLUSIONS

Operational market research using the CBC methodology expands our overall understanding of the recruiting market by providing new information about potential recruits' preferences for the different components of an enlistment package. The data show that respondents with different enlistment propensities have different preferences for the various incentives in the survey. One way to interpret these results is that they suggest there is a need for variable packages that can be targeted to different market segments. However, budgetary considerations and current recruiting difficulties may force the Navy to focus relatively more attention on incentives that have the potential of *expanding* the recruiting market.

For the Navy to expand its recruiting market, it will have to focus more efforts on attracting medium-propensity youth. The results of this study indicate that medium-propensity youth are more likely to favor the path of some college before working. Thus, CNRC must investigate ways to make serving in the Navy competitive with the alternative path of attending college and seeking employment in the private sector after having spent some time in college. More specifically, focusing on college-related incentives—NCF and college credit for Navy training—is likely to be an especially effective means by which to bring in more medium-propensity recruits without spending extra funds on high-propensity recruits who are already entering under existing incentive programs.

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INTRODUCTION

The Navy recruiting mission is becoming more and more difficult. Just as the size of the mission is stabilizing at slightly higher levels after the downsizing, the nation is experiencing the lowest unemployment rates and the highest college enrollment rates since the institution of an all-volunteer force. In response to these conditions, the Navy is planning to fund enlistment bonuses and college incentives at increased levels. To efficiently allocate these increases in funding, however, Commander, Navy Recruiting Command (CNRC) asked CNA to collect and analyze new information about the effects of recruitment incentives on enlistment propensities. Specifically, our task was to use an operational market research approach to address two basic issues. The first is the relationship between enlistment propensity and the various components of an enlistment package. The second is whether these relationships and other survey responses vary according to demographic characteristics.

The study answers the following questions:

- What are the demographic determinants of enlistment propensity?
- Which attributes of the enlistment package are considered most important?
- Does EB or NCF more effectively expand the recruiting market?
- How much must the Navy compensate people to make them indifferent to an additional year of obligated service?
- Can the Navy offer extra incentives to induce recruits to enter less popular occupations?
- Can the Navy compensate people with college credit instead of cash?
- What are the effects of different policy options on enlistment propensity?

Throughout this paper, we focus on ways to expand the existing recruiting pool. To do this, we divide the survey sample into three groups—high, medium, and no propensity. We then highlight the results for the medium-propensity group because it is from this marginal group that the Navy will have to draw to successfully expand its prospect pool.

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WHAT IS CONJOINT ANALYSIS?

Conjoint refers to a family of survey techniques in which respondents indicate their preferences for various products based on their preferences for the variety of features that define those products. The key to conjoint is that products are multi-dimensional rather than one-dimensional. Thus, the name conjoint comes from the words "considered jointly." In this study, we used the technique known as choice-based conjoint (CBC), which requires survey respondents to indicate which of a given set of products they would buy or to indicate "none" if they don't like any of the products.

More specifically, a CBC survey is made up of tasks, concepts, and attributes. Each task entails picking one concept from a given set. The concepts are the hypothetical products from which the respondents must choose. Finally, the attributes are the features that define the concepts, or products, and each attribute has various levels. Most surveys are structured so that a task has three or four concepts, plus a "none" option that allows the respondent to indicate that he or she doesn't like any of the concepts. Figure 1 shows an example of what a CBC task for a survey on cars might look like. The task has three concepts—or three different cars—from which to choose. The concepts each have four attributes: manufacturer, price, color, and miles per gallon (mpg). Each of these attributes has several different levels. For example, manufacturer can be Ford, Lexus, or Toyota, and price can range from $15,000 to $30,000. Although there is an obvious ordering of both the price and mpg attributes from low to high, the make and color attributes cannot be similarly ordered. Finally, there is also a "none" choice: "I would not buy any of these cars."

Figure 1. A CBC task from a hypothetical survey on automobiles

Car #1	Car #2	Car #3	None
Ford $15,000 Blue 20 mpg	Lexus $30,000 Red 25 mpg	Toyota $20,000 Green 30 mpg	I would not buy any of these cars.

Within each CBC survey, each respondent must complete several tasks to give a complete picture of his or her preferences. Regarding the number of tasks, there is a delicate balance between collecting enough data to generate statistically significant results and overloading the respondents with too many decisions. To achieve this balance, the number of tasks in a survey typically ranges from 10 to more than 20.[1]

The data generated from a survey allow inferences to be drawn about people's preferences for different product attributes based on the choices they made on each task—this is why it's called choice-based conjoint. Specifically, the data tell us two important things. The first is which

[1] Johnson and Orme, 1996.

attributes are most important in determining product choice, and the second is how people make trade-offs between the various levels of the different attributes.

CBC is different from other conjoint techniques in the following way. Traditional conjoint surveys ask respondents to explicitly rank or rate the importance of different product attributes. Although this approach was appealing in its directness, it suffered from the fact that people tend to rank all attributes as very important. On a scale of one to ten, most respondents rank most attributes between seven and ten. CBC gets around this flaw by requiring respondents to pick only one product.

THE STUDY DESIGN

CHOICE OF METHODOLOGY AND UNDERLYING ASSUMPTIONS

There are at least two possible approaches to studying the impact of recruitment incentives on people's decisions to enlist in the Navy. The first is an econometric approach using historical data on actual enlistments, and the second is an operational market research approach using stated-preference data. Following the first approach, one can infer which of the available incentives are most popular by analyzing the choices that enlisted Sailors actually made. The appeal of the econometric approach is that it captures historical information about how people facing real choices made binding decisions. Two major drawbacks of using historical data are that it holds no information about people who did not choose to join the Navy, and it cannot be used to evaluate the effectiveness of incentives that have never been offered. An additional drawback of the econometric approach is that, typically, researchers have been able to estimate aggregate effects, but have not been able to identify the individual effects of different incentives and programs of entry.

Following the operational market research approach, we can learn which incentives are likely to bring in the most new Sailors by analyzing potential recruits' stated preferences about which components of the enlistment package they consider most important and which they find most attractive. The main drawback to this approach is that people answering survey questions do not face real consequences associated with their choices. The benefits to using stated-preference data are that they expand the information base to include the preferences of all types of potential recruits and they allow us to collect data on pro-active incentives—that is, incentives that the Navy has never offered before or has just begun to offer, such as higher bonuses, more money for college, and college credit for Navy training.

Although both approaches are necessary to provide a complete picture of the recruiting market, the market research approach is the appropriate approach for this study for the following reasons. First, CNRC wants to know how to use larger financial incentives and new non-financial incentives to expand its share of the employment market. Analysis of these new programs cannot be done using historical data. Second, if the Navy is to expand its recruiting market, it must offer enlistment packages that appeal to those who are not currently choosing to enlist. Assuming that people who aren't joining are different from those who are, it is necessary to collect data on the preferences of people with different enlistment propensities in order to design packages that will appeal to those whose choices can be affected.

Given our choice to use the market research approach, we next had to choose a delivery mechanism for the survey. Specifically, we needed to choose between a pen-and-ink version of the survey or delivering the survey via computer. In the context of current discussions about the increased need for technically skilled Sailors, we wanted to learn more about the preferences of young people with at least some minimum level of computer competency. Therefore, to target this particular sub-sample of the population, we administered the survey on computers.[2]

[2] For more on this issue, see the section on fielding the survey.

THE SURVEY DESIGN

Attributes and attribute levels

The hypothetical enlistment packages in this survey have four different components: a Navy job, a financial incentive, a specified length of obligated service, and an amount of college credit that can be earned as a result of Navy training. The levels of each attribute were chosen to reflect current and future Navy policies and specific Navy needs. Table 1 summarizes the attributes and their levels.

Table 1. Attributes and attribute levels in the CBC Navy survey

Occupation	Obligation length	Financial incentive	College credit
Computer technician	4 years	No incentive	Less than one semester
Engineering technician	5 years	$5,000 EB	One semester
Electronics technician	6 years	$15,000 EB	Two semesters
Submarine technician	8 years	$20,000 EB	Three semesters
Aviation field	--	$30,000 EB	Four semesters
--	--	$30,000 NCF	--
--	--	$50,000 NCF	--
--	--	$70,000 NCF	--
--	--	$10,000 EB & $30,000 NCF	--

We included five broadly designated Navy occupations in the survey: computer technician, engineering technician, electronics technician, submarine technician, or a job in the aviation field. We chose the technician jobs because the Navy was specifically interested in investigating how to recruit people for the technical jobs of the future. The aviation field was considered to be less technical and, therefore, was included as a type of control.

We combined the enlistment bonus (EB) and the Navy College Fund (NCF) to create one attribute called "financial incentive." In the survey, the levels for EB range from $5,000 to $30,000, and the levels for NCF range from $30,000 to $70,000. There is also a mixed incentive with a $10,000 enlistment bonus plus $30,000 for college, as well as no incentive. Currently offered incentives are at the lower end of the range for both NCF and EB. The very high amounts actually exceed what the Navy is now allowed to offer and were included to get information on how effective such large incentives might be for attracting new recruits.[3]

The four levels for obligation length are 4, 5, 6, and 8 years. Note that the Navy does not currently have an 8-year enlistment option; this term length was included to see what the "cost" of such an obligation might be.

[3] At present, the maximum allowable incentive amounts are $20,000 for EB and $50,000 for NCF.

The final attribute is the amount of college credit that can be earned as a result of Navy training. The credit amounts are less than one semester, or one, two, three, or four semesters. College credit was included in the survey to see whether this type of incentive could be effective in attracting some of the 67 percent of high school students who enroll in college immediately after graduation. A recent CNA study found that Sailors who earned college credits while on active duty have higher retention and promotion rates than those who don't, but no one has studied the effect of offering college credit on enlistment propensity.[4] The Navy College Program and Tech Prep are two new Navy programs intended to facilitate the awarding of college credit for Navy training.

Survey tasks

As indicated above, deciding how many tasks respondents should complete is not trivial. If there are too many tasks, respondents are likely to get bored and lose concentration. But if there are too few tasks, there will not be enough data from which to generate statistically significant results. In our survey, each respondent completed 20 tasks, which is slightly on the high side. We chose more tasks rather than fewer because, before fielding the survey, we did not know what the response rates would be and, in CBC analysis, small numbers of respondents can be offset with larger numbers of tasks.

The tasks in the survey were made up of three hypothetical enlistment packages and a "none" option. Respondents were asked to indicate which of the three packages would *most* make them want to join the Navy or to pick "none" if no enlistment package made them want to join. Figure 2 shows how the tasks appeared to the respondents. To generate the three packages that appear in each survey task, the CBC software draws from the different attribute levels according to a specific formula that yields designs that conform to three principles: minimal overlap, level balance, and orthogonality. Minimal overlap means that each attribute level is shown as few times as possible in a given task, and level balance means that each level of an attribute is shown an approximately equal number of times. To satisfy the principle of orthogonality, attribute levels are chosen independently so that each level's effect can be measured independently of all other effects.[5]

Figure 2. An example of a randomly constructed survey task

Package 1	Package 2	Package 3	None
Submarine tech No incentive 4 years 2 semesters	Aviation field $30,000 EB 6 years 3 semesters	Computer tech $70,000 NCF 5 years 1 semester	None of these jobs would get me to join the Navy.

4 Garcia, Joy, and Reese, 1998.

5 Sawtooth Software, Inc., *CBC User Manual, Version 2.0*, pp. 8-4 to 8-7.

FIELDING THE SURVEY

The survey was conducted as a disk-by-mail (DBM) survey.[6] It was sent to 4,400 high school students and 600 community college students in two mailings. The first mailing went out in early January 2000 and the second in mid March 2000.[7] The mailing list for the high school students came directly from CNRC, and the mailing lists for the community college students were procured from Navy Education Specialists from Michigan, North Carolina, Tennessee, and Texas. Mailing lists that identify households with both computers and students in the relevant age group were commercially available, but these lists did not identify the students by first name. Because our target respondents were the students themselves, we did not use these lists. Thus, we chose knowing students' names over knowing they had computers.

The choice to field the survey using DBM was driven by our assumption that the Navy should focus its attention on youth who have some minimum level of computer literacy. The reason DBM is the appropriate method for this target audience is that people who respond to a DBM survey are more likely not only to have access to a computer, but also to be comfortable using a computer. In fact, 95 percent of the respondents did have a computer in the home.

SURVEY RESPONSE RATES

Using cash incentives improves response rates

A current trend in surveying by mail is to include monetary incentives in the survey packets. Several studies conducted by researchers and marketing practitioners have shown that small monetary incentives are a cost-effective way to significantly improve response rates in mail surveys.[8] Thus, to improve our response rate and, at the same time, learn something about the effectiveness of this practice within CNRC's target audience, we sent out the surveys with three different incentives.

In the first mailing, we sent 1,500 packets with a $2 incentive (in the form of a $2 bill), 1,000 packets with a $1 incentive, and 1,500 packets with no incentive. In the second mailing, we sent 500 packets with a $1 incentive and 500 packets with the $2 bills. Table 2 shows how response rates differed by incentive and by mailing. Overall, the response rate for the $1 incentive was twice as large as that for no incentive, and the response rate for the $2 incentive was nearly three times greater. Clearly, including an incentive substantially increased response rates. Furthermore, given our mailing costs, the $2 incentive was the most cost-effective.

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[6] A sub-contractor, ParaTechnologies from Costa Mesa, CA, handled the logistics of the mailing and the collection of the survey packets. The subcontractor also compiled the data from each individual disk into the one large data set that we used for the analysis.

[7] Fielding the survey required special permission from the Office of Management and Budget (OMB). Obtaining this permission increased the duration of the project substantially beyond what was initially projected.

[8] See Brennan and Seymour (1993), James and Bolstein (1992), Wayman (1997), Wilk (1993), and Witt and Bernstein (1996).

Table 2. Survey response rates by incentive amount and mailing

Mailing	Incentive (%) No incentive	$1	$2	Total
Mailing 1	5.5	12.5	15.4	11.0
Mailing 2	--	10.2	15.6	12.9
Total	5.5	11.8	15.5	11.4[a]

a. Seventy-seven of the 5,000 packets sent were returned because they had incorrect addresses. Therefore, the overall response rate is based on a total of 4,923 packets, rather than 5,000.

Although the preponderance of data suggested that incentives would improve response rates, all of the populations from which these existing data were drawn were adult populations. We did not find any data on what to expect in terms of response rates for high-school-aged students or how they might respond to a monetary incentive. Therefore, the data collected here represent new information on behavior for this age group, which will be useful for future mail surveys. Specifically, in CNRC's next project of this type, sending all packets with a minimal incentive will improve the overall response rate substantially.

Response rate bias

Response rate bias occurs when people who respond to a survey are systematically different from those who don't respond. As mentioned above, nearly all of the survey respondents had a computer in the home. This is a much higher rate of computer ownership than is found in the population at large and is a source of skill bias that we created intentionally. However, there may be other sources of bias associated with the DBM delivery mechanism that may not be desirable if they mean that conclusions drawn from the survey data may not hold for a more representative sample. In some cases, it is possible to make some assumptions about the nature of the bias and its likely effects on results. What information we have does not point to any noticeable response rate bias. Specifically, in the next section, we show that enlistment propensities for our sample are not substantially different from those seen in other surveys.

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SAMPLE CHARACTERISTICS

In addition to completing the conjoint survey tasks, our respondents also answered traditional survey questions about their demographic characteristics, as well as more specific questions about their grades while in high school and their plans after graduation. Respondents were also asked to indicate their interest in joining the Navy.[9] The questions regarding interest in the Navy were asked to allow us to divide the sample into different propensity groups and then analyze how preferences differ across these groups. Comparing preferences for people with different stated propensities is a key part of the analysis. The demographic questions allow us to draw conclusions about how demographic characteristics affect propensity as well as preferences. Making these connections is important because it allows us to draw conclusions about how to identify and attract young people who do not belong to the traditional recruiting pool.

ENLISTMENT PROPENSITY

Defining propensity groups

Both before and after completing the conjoint survey tasks, the respondents were asked, "How likely are you to serve in the Navy within the next 2 or 3 years?" Possible answers were: definitely, probably, probably not, and definitely not.[10] Based on responses to these questions, we created three propensity groups—high, medium, and no propensity—which are defined in the following way:

- High-propensity respondents answered "definitely" or "probably" both before and after the conjoint tasks.
- Medium-propensity respondents answered "probably not" or "definitely not" before the conjoint tasks, but answered "definitely," "probably," or "probably not" after the conjoint tasks.
- No-propensity respondents answered "definitely not" after the conjoint tasks.11

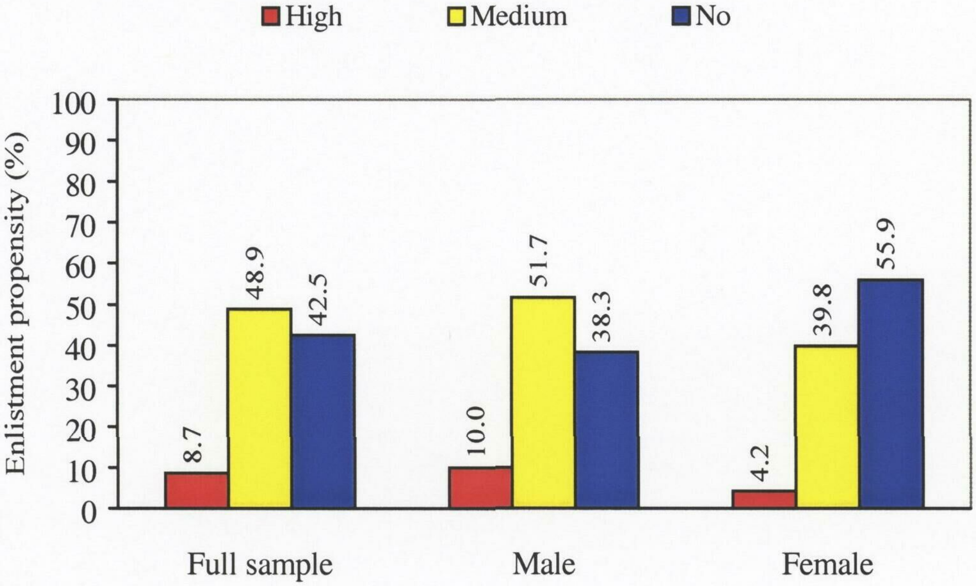
Given the above definitions, figure 3 shows the distribution of respondents across the three propensity groups for the full sample and by gender. The first set of bars shows that just under half of all the respondents (243) are categorized as medium-propensity, while only 9 percent (43) are categorized as high-propensity. The remaining 43 percent of the respondents (211) belong in the no-propensity group. The second and third sets of bars show that 10 percent of male respondents and 4 percent of female respondents have a high propensity.

[9] Appendix A includes a list of the questions asked.

[10] Note that, in our survey, both the question and the possible answers were phrased to match the wording of the propensity question in the Youth Attitude Tracking Survey (YATS).

[11] These decision rules are illustrated later in table 3.

Figure 3. Enlistment propensity for the full sample and by gender



YATS positively propended

1998:
male = 9.3%
female = 5.2%

1990-98 avg:
male = 10.2%
female = 4.7%

Source:
The 1998 YATS, DMDC

These gender-specific propensity rates are roughly comparable with current and past results of the Youth Attitude Tracking Survey (YATS). In the 1998 YATS, the most recent year for which data are available, about 9 percent of males were highly propended and about 5 percent of females were highly propended.[12] The 9-year average, from 1990 to 1998, was 10.2 percent for males and 4.7 percent for females. Thus, male survey respondents have a slightly higher enlistment propensity than the most recent measure of national propensity, but their propensities are comparable to those seen over the decade as a whole. In contrast, the enlistment propensity of female survey respondents is slightly lower than both the recent measure and the 9-year average. Overall, the data suggest that, when it comes to enlistment propensity, the respondents in this study's sample are representative of the youth population as a whole.

Stated propensity before and after the conjoint tasks

Responses to the propensity questions can also be used to learn something about how additional information about potential Navy programs can affect propensity. The data in table 3 show how respondents' stated propensities changed after completing the conjoint tasks. First, none of the respondents who answered "definitely" or "probably" before the conjoint portion of the survey indicated that they were less likely to join the Navy after the conjoint portion of the survey. Second, several of those who answered "probably not" or "definitely not" beforehand became *more likely* to join afterward: 57 of 459, or 12.4 percent, became more likely. In contrast, only 12 of the 218 respondents (5.5 percent) who said "probably not" before the conjoint, said "definitely not" after the conjoint. Thus, to the degree that the Navy can actually offer the incentives included in the survey, these data indicate that additional information about Navy incentives and programs does not cause enlistment propensities to fall, and it may cause them to

12 YATS respondents are asked the propensity question only once; those who answer "definitely" or "probably" are considered "positively propended." This YATS definition corresponds directly to the definition of "high propensity" being used in this study.

rise. This result suggests that efforts to increase the recruiting-age population's awareness of available incentives (e.g., increased advertising) provide benefit at the margin. The benefits of such efforts can be weighed against their costs to determine overall cost-effectiveness.

Table 3. Distribution of responses to the "before" and "after" propensity questions

"Before" propensity	"After" propensity				Total
	Definitely	Probably	Probably not	Definitely not	
Definitely	13	0	0	0	13
Probably	2 ←	28	0	0	30
Probably not	0	16 ←	185	12	218
Definitely not	1	0	41 ←	199	241
Total	16	44	226	211	497

Notes: 1. The total number of responses does not add up to 500 because of missing answers on the "after" propensity question.

2. The separation of the cells with double lines illustrates the decision rules used to create the propensity groups. Cells in the upper left corner identify high-propensity responses; cells in the middle of the table identify medium-propensity responses; and cells in the "definitely not" column identify no-propensity responses.

DEMOGRAPHIC CHARACTERISTICS AND EDUCATIONAL STATUS BY PROPENSITY GROUP

The data in table 4 show how the three propensity groups vary in their basic demographic characteristics. Relative to the medium-propensity group, respondents in the high-propensity group are more likely to be male and African-American or Hispanic/Latino; they are also more likely to be younger than 18 years old. In contrast, respondents in the no-propensity group are more likely to be female and slightly more likely to be older than 18 years. The racial/ethnic mix of the no-propensity group is not substantially different from that of the medium-propensity group.

Given the 11-percent increase in college enrollment rates between 1990 and 1998,[13] the education data in table 5 are intended to give some idea of the relationship between enlistment propensity and both high school performance and post-high-school plans. The data show that nearly 92 percent, or 463, of the survey respondents are high school students and the remaining 8 percent are either high school graduates or high school dropouts. The lower portions of table 5 show how post-high-school plans and high school grades differ by propensity group for the respondents who are currently in high school.[14] Compared to medium-propensity respondents, high-propensity respondents are much less likely to be college bound and, thus, much more likely to be planning to enter the workforce following high school graduation. High-propensity respondents also get substantially lower grades, on average. The differences between

[13] *Digest of Educational Statistics*, 1999, Table 388.

[14] Because the sub-sample of respondents who are not high school students is so small, we cannot show comparable statistics on their post-high-school activities or their high school grades.

Table 4. Demographic characteristics by propensity group

Characteristic	Full sample (%)	Propensity group (%)		
		High propensity	Medium propensity	No propensity
Gender[a]				
Male	76.7	88.4	80.7	68.7
Female	23.3	11.6	19.3	31.3
Age				
17 years	60.8	69.8	60.1	61.1
18 years	32.2	27.9	35.8	30.8
Older than 18 years	6.8	2.3	3.6	7.8
Race/ethnicity				
White	79.8	74.4	79.4	82.5
African-American	6.5	14.0	7.4	3.8
Hispanic/Latino	4.9	7.0	5.3	3.8
Other	8.7	4.7	7.9	9.9

a. The mailing was weighted in favor of males. Our aim was to achieve an 80-20 male-female split in the mailing, but because of incomplete information on the mailing lists, we don't know the exact share of packets that went to each sex. The 77-23 male-female split in the final sample may represent slight differences in response rates by gender or it may reflect the extent to which we missed our 80-20 goal.

Table 5. Educational status, post-high-school plans, and high school grades by propensity group

Characteristic	Full sample	Propensity group		
		High propensity	Medium propensity	No propensity
Education status				
HS student	91.5	95.3	93.4	88.6
HS graduate	6.9	4.7	4.9	9.5
Did not graduate	1.6	0.0	1.6	1.9
Post-HS plans[a]				
2-year college	11.4	4.9	10.1	13.5
4-year college	73.2	63.4	77.1	71.9
2- & 4-year college	1.5	2.4	1.3	2.7
Work only	8.9	24.4	6.6	6.5
Work & school	5.0	4.9	4.8	5.4
High school grades[a]				
Mostly above B's	64.7	42.4	64.2	68.7
Mostly B's & below	35.3	57.6	35.8	31.3

a. These data are for only those respondents who are currently in high school.

medium- and no-propensity respondents are less pronounced. The no-propensity group has relatively more high school graduates, is relatively more likely to be considering a 2-year college than a 4-year college, and gets slightly better grades.

The fact that high-propensity respondents don't do as well in school and are more likely to be minorities can be interpreted to indicate that propensity is related to an individual's assessment of his or her opportunities in the civilian sector. Specifically, people who think they may not fare well in the job market or in college may see the military as an opportunity to get ahead. If this interpretation is correct, these demographic data suggest that the way to attract a new group of recruits is to make the Navy more competitive with civilian jobs and/or to make the Navy more competitive with what colleges provide.

Finally, based on these differences in demographic characteristics, it is reasonable to expect that medium- and no-propensity respondents will have stronger relative preferences for college-related incentives. In fact, the CBC results will show that this is the case.

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METHODOLOGY—THE UNDERLYING BEHAVIORAL AND STATISTICAL MODELS

The point of CBC analysis is to use the preferences contained in the raw survey data to predict how a given set of hypothetical products will fare in the market. To do this, CBC analysis builds on two fundamental assumptions. The first is that products, or jobs, are defined by a whole set of attributes rather than just one attribute. The second is that people implicitly evaluate the total worth of the product by combining the amounts of utility value provided by each attribute individually. Thus, the first step in predicting the market performance of a given product is to estimate the utility values of the individual product attributes. In this study, we estimated the attribute utilities from the survey data using logit regression analysis. The second step is to combine these individual attribute utilities to come up with a measure of the total worth of a product. Given the structure of the logit model, people are assumed to simply add the individual attribute utilities to determine the total utility of a product. The final step is to simulate how people actually choose between various products in the "market place" once they have determined the product values. In this study, we based the market simulations on the "Share of Preference" model, which predicts the percentage of respondents that is likely to choose each product. These percentages are called probabilities of choice or shares of preference.

CONDITIONAL LOGIT AND THE SHARE OF PREFERENCE MODEL

The statistical model used in this study is known in econometrics as a conditional logit model. It is a popular model in CBC analysis for four reasons. First, the logit model is a discrete choice model, which means that it estimates the probability of choosing one alternative from a well-defined set of alternatives, conditional on certain factors. Thus, what distinguishes this model from traditional regression models is that the behavior of interest, or the dependent variable, is characterized by a discrete rather than a continuous variable. Typical examples of discrete choices are whether to participate in the labor force, whether to vote, and whether to make a specific purchase.

Second, the conditional logit model, in particular, is different from other discrete choice models because rather than estimating the effects of respondents' characteristics on the choices they make, it estimates the effects of characteristics of the choices themselves. For example, rather than estimating the effect of a respondent's age on the likelihood that he will pick a certain enlistment package, the conditional logit model estimates the effect of having a $5,000 EB in the package. More generally, consider choosing alternative x_i from a well-defined set of alternatives and let each alternative be defined by K attributes. According to the conditional logit model, the probability that alternative x_i will be chosen is:

$$\text{prob}(x_i) = \frac{\exp(\beta' x_i)}{\sum_i \exp(\beta' x_i)} \quad . \tag{1}$$

In this notation, x_i and β are vectors with K elements that correspond to the K attributes of the product. The β vector measures the impact of each attribute of x_i on the probability that x_i will be chosen.

The third reason the conditional logit model is used is that it allows us to adopt the assumption that people evaluate the overall attractiveness of a choice by summing the utilities associated with each of the attributes of the choice. Under this assumption, the overall utility of choice x_i is a linear function of the attributes of x_i:

$$U_i = \sum_k \beta_k x_{ik} \quad , \tag{2}$$

where U_i is the overall utility of choice x_i; x_{ik} denotes the level of the k^{th} attribute of x_i; and β_k measures the contribution of x_{ik} to U_i. Note, however, that $\sum_k \beta_k x_{ik}$ can be written as $\beta' x_i$ in vector notation. Thus, the conditional logit model of equation 1 includes the assumption of a linear relationship between x_i and U_i and the estimated β's are the utility values of each attribute.

Finally, since the conditional logit model estimates the probability that a given alternative, x_i will be chosen conditional on the attributes of x_i, it serves as the base for the share of preference model for market simulations. Using this model, simulations are done in the following way. First, a set of hypothetical products is defined using different combinations of the attribute levels. Then, the total utilities of all the products in the set are calculated using the utility values that are estimated by the logit regression. These values are then plugged into equation 3 to generate shares of preference or predicted probabilities of choice for each product.

$$\text{prob}(x_i) = \frac{\exp(U_i)}{\sum_i \exp(U_i)} \quad . \tag{3}$$

This method for modeling consumer choice contains a useful and realistic assumption about human behavior. Specifically, it can be shown that within this model, the marginal impact of a given change in any attribute level for the product of interest will be greatest when the probability of choosing the product is equal to 50 percent.[15] The impact of any change diminishes as the probability of choosing the product approaches zero or one. This means that the impact of any change is greatest when the consumer is "on the fence" about choosing it and that the impact of any change is smallest when the consumer's preferences for (or against) the product are very strong.[16]

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[15] Sawtooth Software, Inc., *CBC User Manual, Version 2.0.*

[16] Two additional desirable properties are that it ensures that the probabilities are all positive since the exponentiation of any real number is always positive and that $\text{prob}(x_i)$ does not change if all the utilities are re-scaled by the same constant.

SHARES OF PREFERENCE SIMULATIONS—AN EXAMPLE

To make the theoretical discussion in the previous section a little clearer, we present an example of how to use the estimated coefficients from the conditional logit model to calculate the total utilities of two hypothetical enlistment packages and how to use these utilities to predict the probability of choice for each package. The attribute levels for the two enlistment packages and the utilities associated with each level are shown in the first four rows of table 6.[17]

Table 6. Calculating predicted probabilities of choice—an example

Enlistment package 1		Enlistment package 2	
Attribute / level	Logit-estimated utility	Attribute / level	Logit-estimated utility
Computer	0.247	Submarine	-0.530
4 years	0.616	6 years	-0.120
$20K EB	0.107	$50K NCF	0.408
3 semesters	0.226	<1 semester	-0.384
total package value - U_i	**1.196**	**total package value - U_i**	**-0.626**
exp(U_i)	**3.307**	**exp(U_i)**	**0.534**
predicted probabilities of choice	**86%**	**predicted probabilities of choice**	**14%**

Note: These utilities come from estimating the logit model for the medium-propensity sub-sample in this study. This output is reported later in table 7.

Following equation 3, the first step in calculating probabilities of choice is to calculate the total utilities for both packages by summing the individual utility values for each attribute (i.e., calculate U_i for each x_i). The next step is to exponentiate the total product values for both products in the simulation scenario. These values are reported in rows 5 and 6 of table 6. Finally, the probabilities of choice are calculated by summing the exponentially transformed product values and then calculating each value's percent of the total. The sum of the exponentiated utilities is 3.841, which yields predicted preference shares of 86 percent for package 1 (3.307/3.841 = .86) and 14 percent for package 2 (0.534/3.841 = .14). Thus, the simulation in this example tells us that, if forced to pick between the two packages in the scenario, 86 percent of respondents would pick package 1 and 14 percent would pick package 2.

[17] The utility values come from logit estimates that were generated using the medium-propensity sub-sample. The complete logit estimation results are reported later in table 7.

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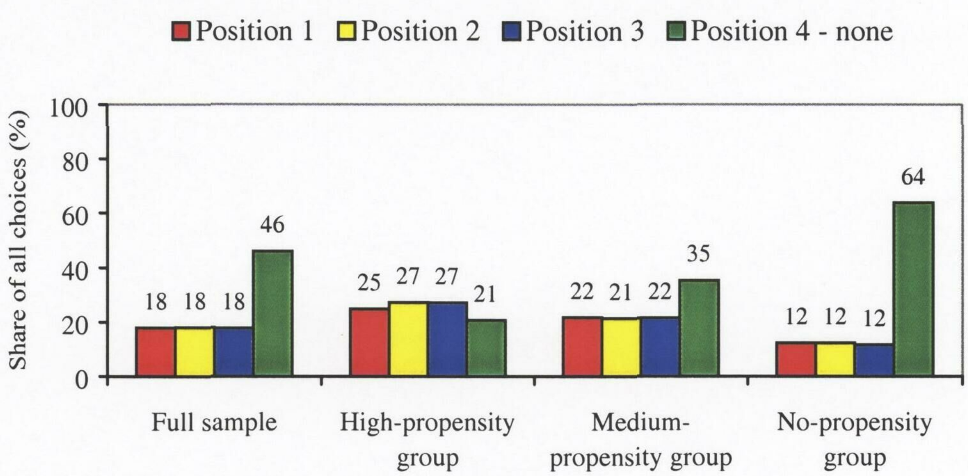
UNDERLYING DATA AND ESTIMATION RESULTS

Before moving on to the simulation analysis that is the primary output of CBC, we present some of the data on which the simulations are based. First, we show the rates at which respondents picked packages in each concept position, and second, we present logit estimation output for the medium-propensity sub-sample. These data show that the values underlying the simulations are reasonable and statistically significant.

CONCEPT POSITION BIAS BY PROPENSITY GROUP

On each task in our survey, the respondents were asked to choose one of three enlistment packages or to choose "none," thus indicating that none of the three packages would make them want to join the Navy. Figure 4 shows the rates at which respondents in the whole sample and in each of the three propensity groups chose "none," as well as the rates at which they chose enlistment packages in each of the other three positions of the survey tasks. These data show that choices were evenly distributed across positions 1, 2, and 3 in the survey, which indicates that the survey results are not driven by the position in which the package concept appeared. In other words, there is no bias associated with concept position. (Note that the distribution of choices across positions 1, 2, and 3 is not as even for the high-propensity group as for the others. This could have occurred randomly because there are so few people in this group.)

Figure 4. Survey responses by concept position and by propensity group



LOGIT OUTPUT

Table 7 shows the output from the logit model that was estimated using data from the medium-propensity sub-sample.[18] The overall fit of the model is evaluated by a chi-squared (χ^2) statistic, which compares the value of the log likelihood function that would be obtained if all the effects

[18] The same output tables for the full sample and the high- and no-propensity sub-samples are in appendix B.

were zero with the log likelihood that is obtained from the data. In this case, the χ^2 statistic is significantly different from zero, indicating that the overall model provides a fit that is significantly better than what would be expected at random.

Table 7. Logit output for the model estimated using the medium-propensity sub-sample

	Attribute-level	Effect (std. dev.)
	Rating	
1	Electronics	-0.0224 (0.04097)
2	Computer	0.2466 (0.03882) ***
3	Engineering	0.1517 (0.03956) ***
4	Submarine	-0.5304 (0.04685) ***
5	Aviation	0.1544 (0.04254) ***
	Length of obligation	
6	4 years	0.6165 (0.03180) ***
7	5 years	0.2735 (0.03355) ***
8	6 years	-0.1202 (0.03650) ***
9	8 years	-0.7698 (0.04417) ***
	Incentive	
10	\$5K EB	-0.6510 (0.07252) ***
11	\$10K EB	-0.2783 (0.06456) ***
12	\$20K EB	0.1072 (0.05806)
13	\$30K EB	0.3156 (0.05575) ***
14	\$30K NCF	-0.0101 (0.05991)
15	\$50K NCF	0.4080 (0.05479) ***
16	\$70K EB	0.6433 (0.05271) ***
17	\$10K EB & \$40K NCF	0.5468 (0.05384) ***
18	No incentive	-1.0815 (0.08510) ***
	College credit	
19	<1 semester	-0.3842 (0.04487) ***
20	1 semester	-0.1743 (0.04236) ***
21	2 semesters	-0.0608 (0.04146)
22	3 semesters	0.2258 (0.03896) ***
23	4 semesters	0.3936 (0.04041) ***
24	None	0.7271 (0.03313) ***

Notes: 1. There are files built for 240 respondents and data for 4,800 choice tasks.
2. χ^2 = 1702.44550; pseudo R^2 = 0.879922.
3. *** indicates significance at the .01 level.

The estimated coefficients are the model's estimates of the utility values associated with each level of each attribute. Within each attribute, the coefficients sum to zero so that the impact of each level is measured relative to the impact of the other levels within the attribute.[19] A large positive utility value indicates that an attribute level is highly preferred relative to the other levels. Conversely, a large negative value indicates than an attribute level is not preferred relative to the other levels.

Finally, with logit, it is also possible to estimate the effects of interactions between variables. Models with interactions were estimated for each sub-sample and for the full sample, but in no case were any of the interactions statistically significant. A larger sample size than 500 respondents would have been needed to estimate the interactions, given that a substantial number of respondents picked "none" on every task in the survey.

[19] The utilities sum to zero because one attribute level is omitted during estimation. The utility value for the omitted level is assigned after estimation and is equal to the negative sum of the other utilities.

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ATTRIBUTE "IMPORTANCES"

One of the key questions we are trying to answer with this study is which components of the enlistment package are most important. Although we will use simulation results to draw inferences regarding attribute importance, it is also possible to directly measure importance by comparing the maximum contributions the four attributes can make to the total utility of a product. Specifically, the contribution of a given attribute depends on the range of the attribute's utility values. The formula used to calculate the importance of attribute k of K attributes is:

$$I_k = \frac{\max U_k - \min U_k}{\sum_{j=1}^{K} (\max U_j - \min U_j)}, \tag{4}$$

where I_k is the importance of attribute k, and $\max U_k$ and $\min U_k$ are attribute k's maximum and minimum utility values, respectively. In words, the formula translates the ranges of each attribute's utility values into percentages and yields a set of importance values that sum to 100 percent.[20]

Figure 5 shows the average importance of each attribute for respondents in the three propensity groups. As expected, incentive is the most important attribute for all three groups, but its relative importance varies substantially by enlistment propensity. For the high-propensity group, incentive is more than twice as important as the second-ranked attribute. In contrast, for the medium- and no-propensity groups, the measured importances of incentive level exceed the measured importances of the second-ranked attribute—length of obligation, for both groups—by only 25 and 20 percent, respectively. Thus, incentive has a greater impact on choice of enlistment package for high-propensity respondents than for medium- and no-propensity respondents.[21]

For both the medium- and no-propensity groups, length of obligated service is ranked as the second most important attribute. As noted above, term length is nearly as important as incentive for respondents in both these groups. For high-propensity respondents, however, term length ties with college credit as least important. Furthermore, the measured importance of obligation length is nearly twice as large for the medium- and no-propensity groups as it is for the high-propensity group.

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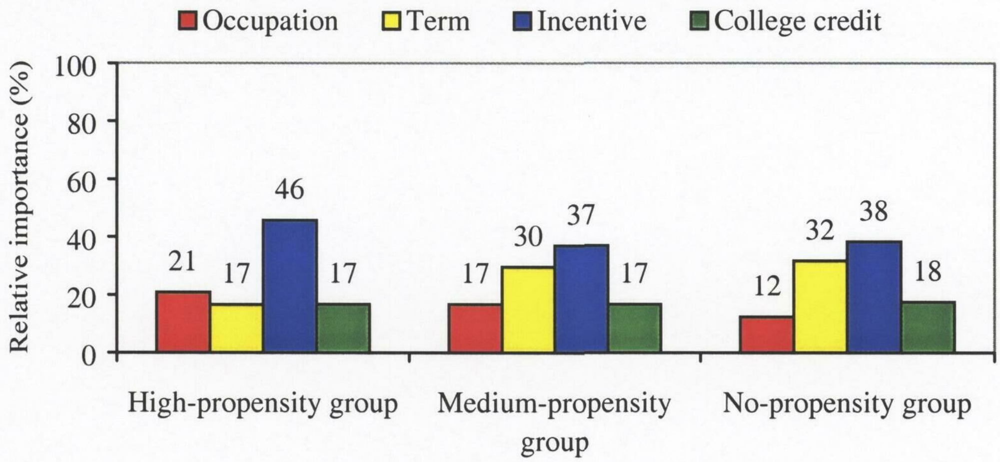
[20] Because two potential issues arise when using attribute importances, care must be taken when drawing conclusions from importance data. The first problem is the tendency for attributes with more levels to have greater measured importance than those with fewer. This is known as the "number-of-levels effect." It can be addressed by comparing importances across propensity groups, rather than analyzing the absolute attribute rankings for any one group. The second problem comes from the fact that utilities are averaged across heterogeneous respondents so that extreme preferences at opposite ends of the scale may cancel each other out. Again, looking at importances by propensity groups helps to eliminate this aggregation effect because it reduces respondent heterogeneity for each group. These issues are discussed in more detail in appendix C.

[21] This is true regardless of any number-of-levels effects.

Figure 5. Average attribute importances by propensity group



Occupation is ranked a distant second for the high-propensity group and ties for least important with college credit for the medium-propensity group. Occupation is also ranked least important for the no-propensity group—indeed, college credit is measured to be 40 percent more important than Navy job for no-propensity respondents.

Finally, college credit ties for least important for both the high- and medium-propensity groups. However, credit is ranked third most important for the no-propensity group—higher than occupation.

IMPLICATIONS

The importance data show that incentive level (and type) is a relatively important driver of choice for high-propensity respondents. This result is interpreted to indicate that, for people who have already decided they may want to join the Navy, a larger monetary incentive simply makes a desirable option more attractive. Another way to look at it is that these respondents have already decided that a long commitment is not an impediment to enlistment and that they want a career in the Navy regardless of the specific job they fill. Therefore, the relevant feature of any enlistment package will be monetary compensation. The implication of this result is that the Navy's current recruiting strategies and incentives work well for high-propensity recruits: bring them in with financial incentives and assign ratings later.

For the medium- and no-propensity groups, length of obligation is almost as important as incentive level. This is not a surprising result when it is combined with recent data on college completion rates. Although the rate at which high school students go straight to college has increased, the dropout rates for both 2-year and 4-year institutions are high. For 4-year colleges and universities, 27 percent of first-year students do not return for a second year. For 2-year colleges, the figure is 45 percent.[22] In this culture, it is quite likely that young people will resist

[22] Source: ACT press release. Note that for 2-year colleges, this figure includes adults and continuing education students, as well as recent high school graduates.

making the long-term commitment required by the Navy. The data also indicate that college credit is relatively more important for low-propensity young people than for those who have high propensity. Together, the relative importances of obligation length and college credit indicate that people in the medium- and no-propensity groups may be interested in the extra benefits that come with a short-term stint in the Navy; for this group, military service may be a means to an end rather than an end in itself.

In terms of recruiting strategy, the message is to offer college-related incentives and short obligations. To target medium-propensity youth, it would be beneficial for recruiting to increase this population's awareness of college-related incentives like the NCF, the Navy College Program, and Tech Prep. In addition, it would be unwise to try increasing obligation lengths much beyond current levels. Or, in cases where recruiters are trying to draw medium-propensity prospects into ratings with long enlistment terms, extra monetary compensation might be offered. We will investigate the latter option with the CBC simulations.

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SIMULATION RESULTS—PROBABILITIES OF CHOICE

CBC simulations use the CBC survey data to generate quantitative measures of respondents' relative preferences for concepts with different combinations of attribute levels. Specifically, for a given set of concepts, the simulations predict the proportion of respondents who would choose each concept in the simulation if they were forced to choose one or another. These predicted proportions are called probabilities of choice or shares of preference, and, within any given simulation, they sum to one.

In this study, we conducted two types of simulations. First, we conducted simulations that did *not* include a "none" option. Technically, these simulations ignored the question of whether people will actually join the Navy and were used primarily to examine the trade-offs people make between the different components of the enlistment packages. However, we also used them to draw some conclusions about the relationships between enlistment propensity and recruitment incentives. Specifically, we did identical simulations for all three propensity groups and analyzed how predicted preference shares differ across these groups. We focused on results for the medium-propensity respondents because their preferences best represented the preferences of the audience the Navy must reach in order to recruit more successfully.

Second, we designed simulations that *did* include a "none" option. We based these simulations on the full sample logit results, and we used them to predict how changes in the components of different enlistment packages affected the likelihood of choosing a Navy option instead of the "none" option. Including the "none" option allowed us to examine the relationships between enlistment propensity and recruitment incentives more directly than we could with the first set of simulations. Specifically, we mapped changes in the predicted probability of choosing a Navy option to predicted changes in enlistment propensity. Note, however, that we were not predicting changes in the number of enlistments. To do that type of forecasting would have required an extra step in which predicted changes in propensity were used with fuller models that incorporated other aspects of the enlistment decision, such as the option to serve in a different branch of the military, private sector job opportunities that may be higher paying, the actual availability of a rating, the respondents' qualifications, the effectiveness of the recruiting force, the effectiveness of the advertising campaign, and overall awareness.[23]

TRADE-OFFS BETWEEN ATTRIBUTES

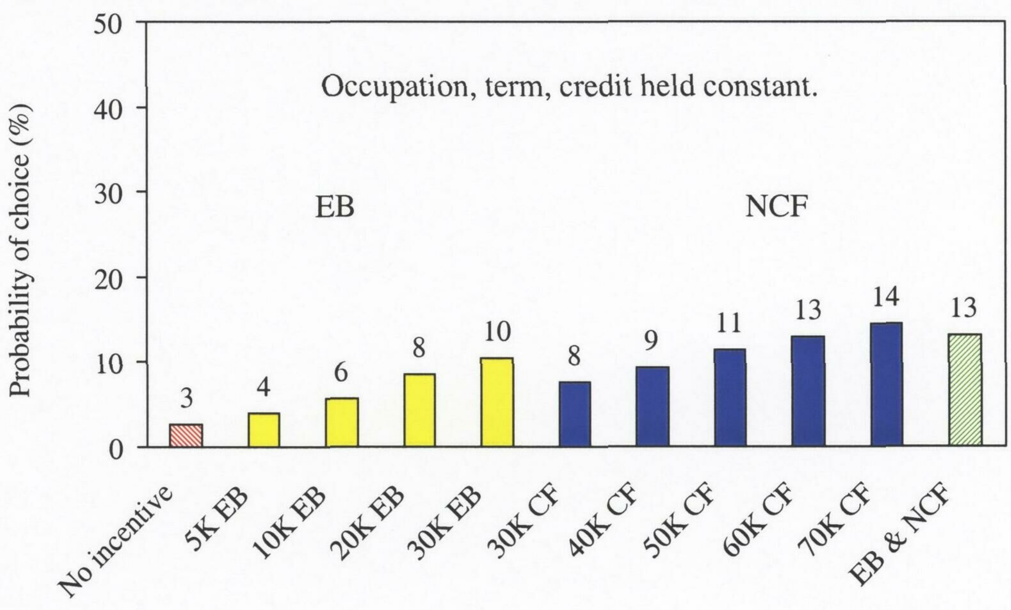
The simulations in this section are structured in the same manner as the two-concept example illustrated in table 6 in that they do not include a "none" option. They differ from the example only in that they may include several concepts rather than just two. Because these simulations do not include a "none" option, they are used to examine relative preferences for the different attributes of enlistment packages and the trade-offs respondents make between these attributes. First, we compared relative preferences for EB and NCF and then we looked at the trade-offs between the non-financial attributes and different EB amounts.

[23] See appendix D for more information on interpreting simulation results.

EB vs. NCF

Figure 6 shows the medium-propensity group's relative preferences for all incentives. At first glance, these data reveal the obvious: people prefer more money to less. Within incentive type, probabilities of choice are strictly increasing with incentive amount and the very large college fund offerings are the most likely to be chosen overall. Specifically, the four most highly preferred incentives are $70,000 for college, the mix of enlistment bonus and college fund, $50,000 for college, and $40,000 for college, in that order. However, in addition to illustrating that more is better, the figure also includes information about the trade-offs between EB and NCF. Focusing on the middle five stovepipes—$20,000 enlistment bonus through $50,000 for college—the data show that medium-propensity respondents prefer a $20,000 bonus over $30,000 for college and a $30,000 bonus over $40,000 for college. These results reflect not only the fact that money for college may not be valuable to all respondents, but also that $30,000 today is worth more than $30,000 a few years from now. These same respondents, however, prefer $50,000 for college over a $30,000 bonus. Together, these results mean that for medium-propensity respondents, it is necessary to promise somewhere between $10,000 and $20,000 more in future money for college than in unrestricted cash up front to overcome natural discounting.[24]

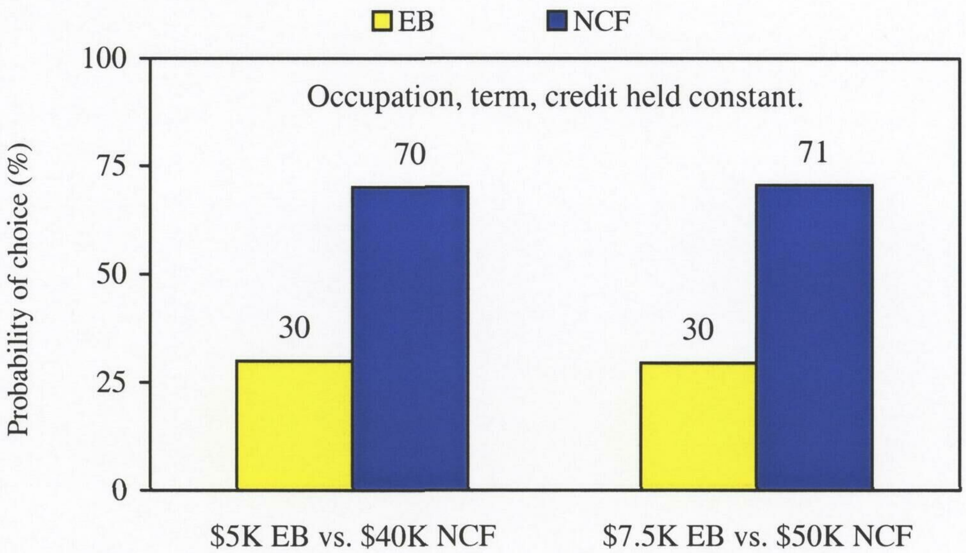
Figure 6. Relative preferences for incentive type and level for the medium-propensity group



[24] Note that the probabilities of choice depicted in figure 6 should not be interpreted to mean that, for example, 3 percent of people would choose an enlistment package with no financial incentive over one with some financial incentive, all else equal. Instead, the simulation results show how much more *extra value* the respondents place on larger incentives. It is important to keep this in mind when interpreting the results of simulations that compare enlistment packages that differ across levels of only one attribute that has an obvious value ordering.

To determine how these preferences translate to cost-effectiveness of the two programs, we compared the rates at which respondents are predicted to choose college fund incentives over actuarially equivalent enlistment bonuses. Focusing on actuarially equivalent amounts allowed us to compare the true costs of the EB and NCF programs by accounting for the difference between what the Navy promises to pay in college fund awards and what is actually claimed by enlistees.[25] Figure 7 shows the results of two separate simulations. The first compares preferences for a package with $40,000 NCF with preferences for a package with an actuarially equivalent EB of $5,000. The second compares preferences for packages with $50,000 NCF and $7,500 EB. The data show that medium-propensity respondents are more than twice as likely to pick an enlistment package with a college fund than to pick a package with an actuarially equivalent bonus.[26]

Figure 7. Relative preferences for actuarially equivalent incentives (EB vs. NCF) for the medium-propensity group



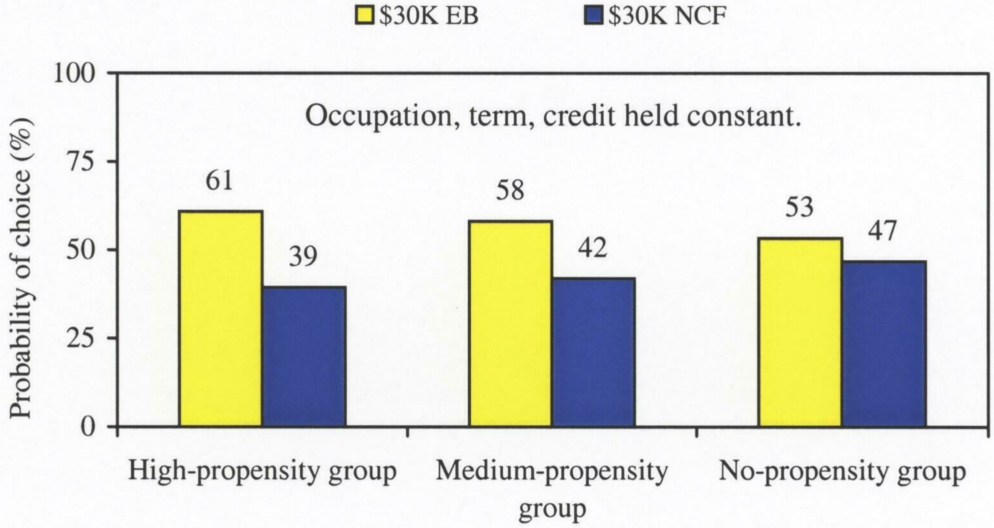
Comparing preferences across propensity groups also yields interesting information about preferences for enlistment bonuses versus the college fund. Specifically, lower-propensity respondents have stronger relative preferences for money for college. This feature of the data can be demonstrated with a direct comparison of preferences for a $30,000 bonus relative to preferences for $30,000 for college. As mentioned above, we expect cash up front to be preferred over delayed cash for college because we expect all respondents to have positive discount rates, regardless of their relative valuations of college tuition assistance. For each propensity group, figure 8 shows predicted preference shares given the choice between an enlistment package with a $30,000 bonus and a package with $30,000 for college. As expected, all groups are more likely to pick the package with the bonus than the one with the college fund, but the data show that the rate at which respondents prefer the bonus decreases as propensity

[25] Data on actuarial equivalency were supplied by CNRC via e-mail.

[26] Because the two sets of stovepipes show the results of two separate simulations, it is not meaningful to compare the 30-percent probability of choice for $5,000 EB with the 30-percent probability of choice for the $7,500 EB.

decreases. High-propensity respondents are 56 percent more likely to choose a bonus, medium-propensity respondents are 38 percent more likely to choose a bonus, and no-propensity respondents are only 13 percent more likely to choose a bonus.

Figure 8. Direct comparison between EB and NCF of equal amounts by propensity group



The result depicted in figure 7 indicates that NCF is likely to be a more cost-effective recruiting tool than EB. Combining this result with that of figure 8 indicates that NCF will be an especially effective means of attracting medium-propensity recruits, thereby expanding the recruiting pool.

Length of obligated service

As we discussed in the section on attribute importances, the preference data gathered for this study indicate that the military's requirement for long, binding commitments is a significant factor in the decision to enlist or not to enlist. Figure 9 shows how the probability of choosing a given enlistment package decreases as the years of obligated service increase for each propensity group. The fact that the curves for the medium- and no-propensity groups decrease more steeply than does the curve for the high-propensity group is another way of showing that an additional year of required service has a greater impact on the choice of someone with lower propensity than on that of someone with higher propensity.

To give an idea about how much respondents prefer shorter enlistments over long enlistments, the data in figure 10 show how much extra medium-propensity recruits must be paid to make them indifferent between serving 5 or 6 years instead of only 4 years. The first set of stovepipes shows that when the same $5,000 EB is given for every obligation length, medium-propensity respondents prefer 4 years to 5 years and 5 years to 6 years. The second set of stovepipes shows that if the EB offered for 5 years is increased to $10,000, or to twice the amount of the 4-year bonus, respondents are indifferent to serving the extra year. Finally, the third set of stovepipes shows that if the bonus offered for a 6-year term is increased to $20,000, or four times more than the 4-year bonus and twice the size of the 5-year bonus, respondents are indifferent between serving 4, 5, or 6 years. We can now use these amounts to calculate the cost per year of each obligation length in terms of EB dollars:

$5,000 EB for 4 years ⇒ a cost of $1,250 per year
$10,000 EB for 5 years ⇒ a cost of $2,000 per year
$20,000 EB for 6 years ⇒ a cost of $3,333 per year.

Figure 9. Preferences for obligation length by propensity group

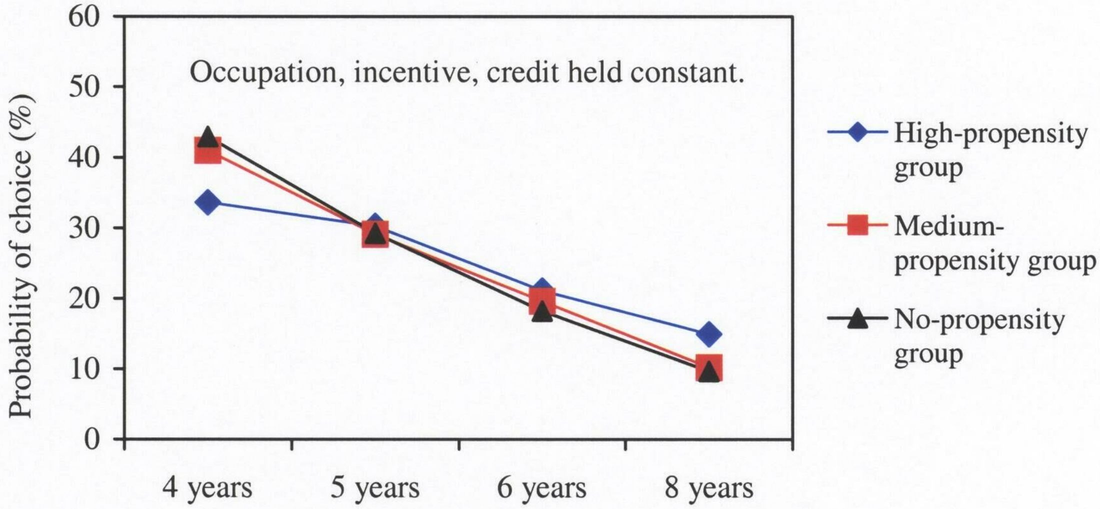
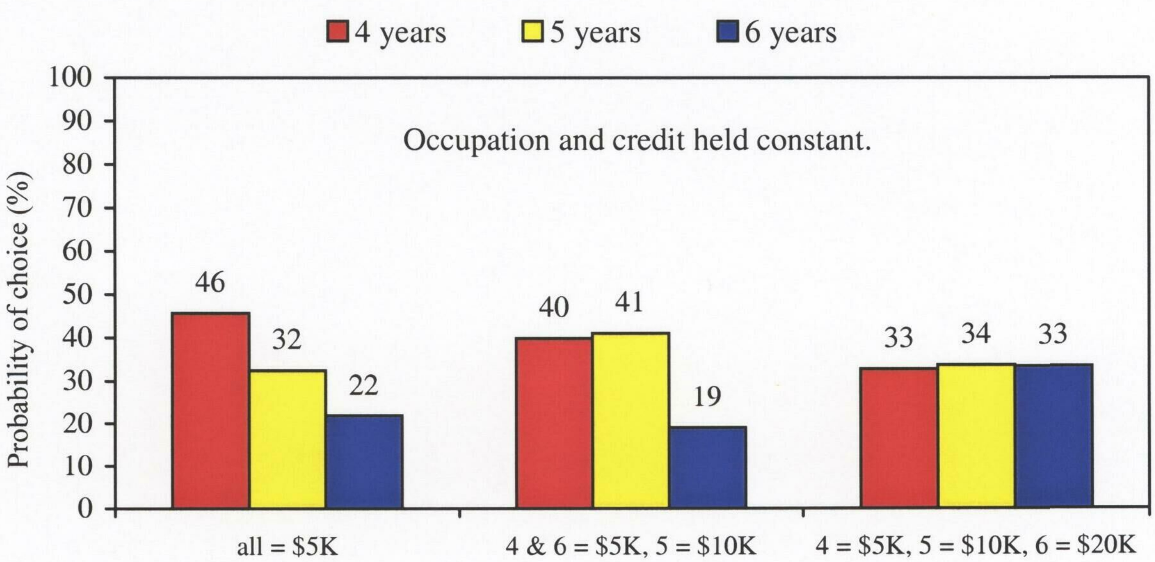


Figure 10. Trade-offs between a larger bonus and one additional year of obligation for the medium-propensity group

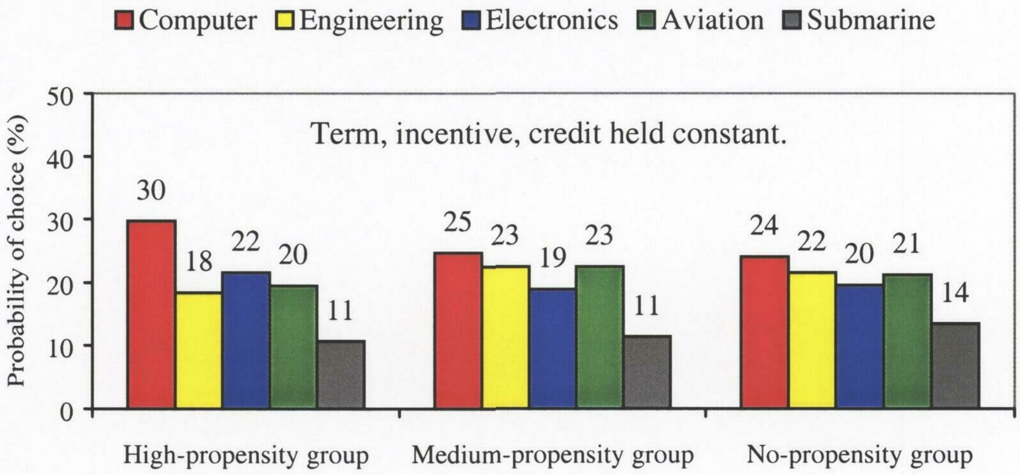


More generally, the EB cost of a 5-year commitment is 1.6 times that of a 4-year commitment, and the EB cost of a 6-year commitment is 2.7 times that of a 4-year commitment. These data can be combined with data on the benefits associated with an additional year of obligation to draw conclusions about the cost-effectiveness of increasing obligation lengths.

Occupation

The data in figure 11 show each group's relative preferences for the five occupations in the survey. Computer technician is the most popular job for all propensity groups, but this preference is stronger for the high-propensity group than for the others. Likewise, submarine technician is the least popular job for all groups. Among the other three occupations, medium- and no-propensity respondents prefer engineering and aviation over electronics, while high-propensity respondents prefer electronics.

Figure 11. Probabilities of choice for occupations by propensity group

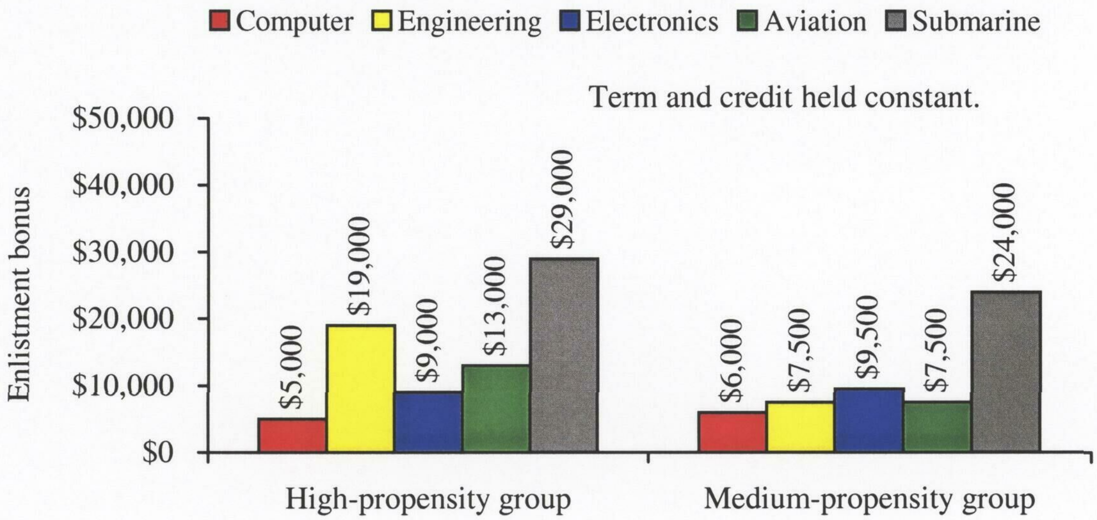


Given that the Navy is interested in getting people to enlist under specific ratings, how can it use its monetary offerings to change preferences and, therefore, probabilities of choice? As a purely academic exercise, we looked at incentive structures that yield equal probabilities of choice for each occupation and for each propensity group. This exercise was considered academic in that the range of choices captured in the survey is very narrow; there are many Navy ratings for which we did not collect any information. Thus, if respondents had been allowed to consider the actual array of occupations available in the Navy, their relative preference structures might have looked quite different.[27] However, it is still possible to learn something about what it might take to compensate a recruit for joining in a rating that is not his first choice. The data also give some useful information on which groups may be most effectively targeted.

[27] A second factor to consider is the fact that some recruits may want, or prefer, rating assignments for which they cannot qualify. This limitation is particularly relevant for the technical ratings we tried to model in this survey.

Figure 12 shows the rating-specific enlistment bonuses that yield equal probabilities of choice for each rating and for the medium- and high-propensity groups, with length of obligation and amount of college credit held constant. The data show that, for the most part, it is not necessary to offer huge differentials to change people's preferences, especially for the medium-propensity group. This is consistent with the importance data that indicated that rating is not considered the most important attribute of an enlistment package. The two exceptions are the large bonuses necessary to make people indifferent to the choice between service as a submarine technician and service in the other ratings and the relatively large bonus differentials that are required to steer high-propensity respondents away from their most preferred ratings. In the first case, the large premium required for submarine technician reflects the strong antisubmarine preferences that show up in these data. However, this may not be a problem since the Navy's requirements for Sailors in the technical submarine ratings appear to be relatively small.[28] In the second case, the larger differentials for the high-propensity group are consistent with the importance data that showed that rating is relatively more important for these respondents than for lower-propensity respondents.

Figure 12. Enlistment bonuses that yield equal probabilities of choice for each occupation



The analysis presented here indicates that it is possible to use financial incentives to affect a recruit's willingness to enlist in the Navy and be assigned to a rating that is not his first choice. An additional implication is that if choice of rating assignment is also an important determinant of a recruit's eventual attrition/retention behavior, it may prove cost-effective to use bonuses and the college fund to steer people into the ratings that the Navy most needs to fill.

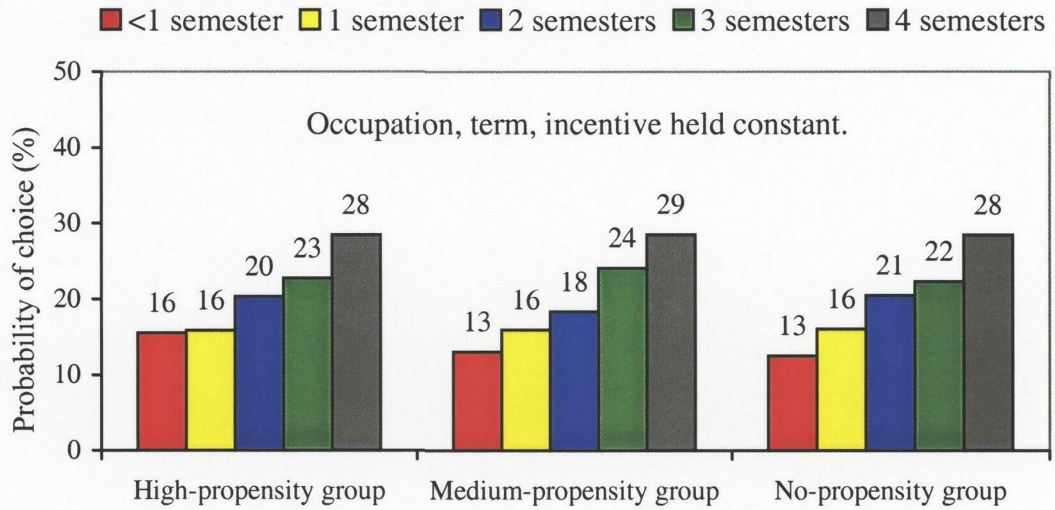
College credit

As with the other attributes, the discussion of college credit begins with a presentation of the relative probability that a given enlistment package will be chosen conditional on the amount of

[28] It is also the case that submariners are already the highest paid since they get both submarine and sea pay, relatively high SRBs, and fast advancement.

college credit it includes and holding everything else constant. These data, presented in figure 13, show that more is better for college credit, just as it is for monetary incentives. The data also show that the relative probabilities of choice don't vary much according to propensity group, although the relative importance of college credit as an attribute did vary with propensity. In particular, recall that college credit was more important than occupation for the no-propensity group.

Figure 13. Probabilities of choice for college credit by propensity group

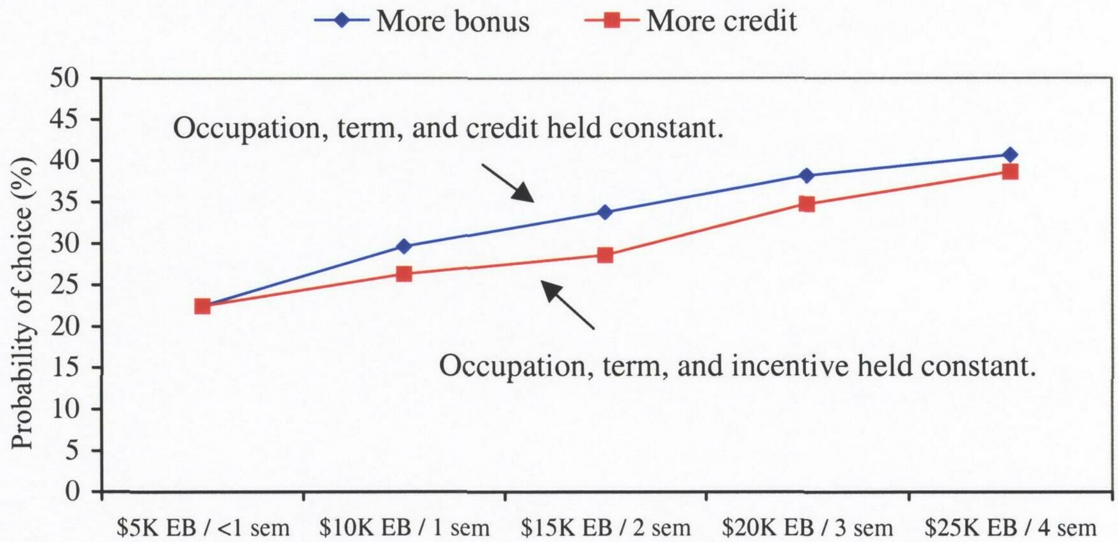


A more interesting question to ask is, "How much is one college credit worth?" In figure 14, we compare the effect of increasing EB in increments of $5,000 with the effect of offering an additional semester of college credit, holding all else constant. The figure shows that, for medium-propensity respondents, the effect of increasing college credit from less than one semester to two semesters is comparable to the effect of increasing EB from $5,000 to about $9,000. Thus, we can measure the EB equivalent value of offering one or two semesters to be about $2,000 per semester. Increasing college credit beyond two semesters has an even greater impact. Going from less than one semester to three semesters has a slightly larger effect than increasing EB from $5,000 to $15,000, and going from less than one semester to four semesters has about the same effect as increasing EB from $5,000 to $20,000. Thus, the EB equivalent value of offering a third and fourth semester is about $5,000 per semester.

These results suggest that giving college DEP scholarships of $2,000 to $4,000 is likely to be a cost-effective recruiting tool.[29] Furthermore, these results can be used to calculate the cost-effectiveness (in terms of recruiting) of offering different college programs like the Navy College Program and Tech Prep.

[29] CNRC will be submitting a proposal to offer college scholarships for attending classes during DEP as part of the FY02 Unified Legislative and Budgeting (ULB) process. This program will be especially cost-effective if attending college courses during DEP reduces Navy academic attrition later.

Figure 14. Offering more credit vs. offering more money for the medium-propensity group



A NAVY OPTION VS. THE "NONE" OPTION

The simulations in this section are designed differently from the simulations in the previous section because they include a "none" option. Including "none" allows us to estimate how likely people are to choose any of the packages in a given set versus how likely they are to choose "none." Structurally, including the "none" option limits the number of concepts that can be included in each scenario because, in CBC simulations, the share of respondents predicted to choose "none" will be correct only if the number of products in the simulations is the same as the number of products in the survey's choice tasks. Therefore, all the scenarios include three enlistment packages and a "none" option.

The simulations entail comparing base case scenarios that are intended to represent current conditions with alternative scenarios that represent different policy options. The alternative scenarios were created by altering the levels of the four attributes of the enlistment packages one at a time and in various combinations. The restriction on the number of concepts in each scenario required us to create multiple base cases. In one set of base cases, the occupations in the three enlistment packages are computer technician (a popular technical rating), aviation field (a less technical rating), and submarine technician (an unpopular technical rating). In the other set of base cases, the occupations in the three packages are computer technician, aviation field, and engineering technician. Simulations with engineering technician were done so that we could analyze the effects of offering large incentives while maintaining a rating-specific incentive structure that is somewhat realistic. For each of these sets of enlistment packages, we constructed two different base cases—one using EB and one using NCF.

Table 8 shows the enlistment packages in the base cases and in three of the alternative scenarios. For both sets of simulations, the EB and NCF entries in the base case scenarios are intended to represent enlistment options that are currently available in the ratings that most closely correspond to the occupations named in the survey.[30] The alternative scenarios are intended to represent specific policy alternatives that the Navy may be interested in evaluating. The scenarios in which the amount of college credit is increased are intended to reflect the amount of credit that might actually be allowed for the training associated with the appropriate ratings. The scenarios in which the amounts of the financial incentives are increased are intended to simulate the effects of increasing incentives to their current legal maximums and beyond, while maintaining the current rating-specific structure. Finally, the scenarios in which obligation length is increased simply allow us to quantify the impact of adding an additional year to the base case obligation.

Table 8. Base case and alternative simulation scenarios

	Obligation	Occupation	EB	NCF	College credit
Base case					
Package 1	4 years	Computer	$10,000	$40,000	<1 semester
Package 2	4 years	Aviation	$5,000	$30,000	<1 semester
Package 3 -- sub	5 years	Submarine	$10,000	$40,000	<1 semester
Package 3 -- eng	4 years	Engineering	$12,000	$50,000	<1 semester
None	--	--	--	--	--
Increase credit					
Package 1	4 years	Computer	$10,000	$40,000	2 semesters
Package 2	4 years	Aviation	$5,000	$30,000	1 semester
Package 3 -- sub	5 years	Submarine	$10,000	$40,000	2 semesters
Package 3 -- eng	4 years	Engineering	$12,000	$50,000	3 semesters
None	--	--	--	--	--
Increase incentive					
Package 1	4 years	Computer	$20,000	$50,000	<1 semester
Package 2	4 years	Aviation	$10,000	$40,000	<1 semester
Package 3 -- sub	5 years	Submarine	$20,000	$50,000	<1 semester
Package 3 -- eng	4 years	Engineering	$25,000	$60,000	<1 semester
None	--	--			--
Increase obligation					
Package 1	5 years	Computer	$10,000	$40,000	<1 semester
Package 2	5 years	Aviation	$5,000	$30,000	<1 semester
Package 3 -- sub	6 years	Submarine	$10,000	$40,000	<1 semester
Package 3 -- eng	5 years	Engineering	$12,000	$50,000	<1 semester
None	--	--	--	--	--

[30] For computer technician, the corresponding rating is AECF; for submarine technician, the rating is SECF; and for engineering technician, the rating is NUC. For the aviation field, the rating could be any one of the following: ABE, ABF, ABH, AD, AE, AK, AM, AME, AO, AS, or AT.

To estimate the impact of these changes in the enlistment package on enlistment propensity, we first used utility values from the logit model that was estimated using the full sample to calculate the change in the probability that a Navy option will be chosen instead of the "none" option (i.e., we summed the probabilities of choice for packages 1, 2, and 3). Table 9 reports these probabilities and changes in these probabilities. The data show that, in all four cases, offering the maximum realistic amount of college credit for Navy training has the single greatest impact on the likelihood of picking a Navy option rather than picking "none." The impact of offering more credit is larger in the engineering scenarios because of the underlying structure of preferences for college credit. Specifically, the difference between the utilities of three semesters and two semesters is greater than the difference between the utilities of two semesters and less than one semester. This difference is reflected in the engineering scenarios, but not in the submarine scenarios because the maximum amount of credit offered in the latter is only two semesters.

Table 9. The predicted probability of choosing a Navy option instead of "none" and percent changes in those probabilities relative to the base case

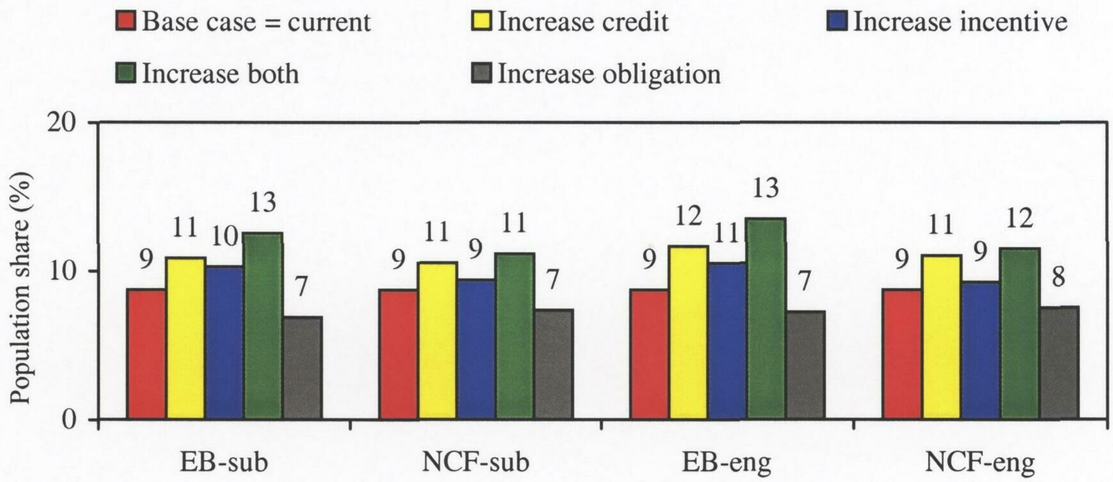
	Predicted probability of choosing a Navy option (%)		Change in the predicted probability (%)	
Scenario	Submarine	Engineering	Submarine	Engineering
Base case – EB	38.0	40.3	--	--
Increase credit	47.4	54.0	24.7	34.0
Increase EB	44.9	48.6	18.1	20.7
Increase both	54.7	62.5	44.1	55.1
Increase obligation	30.0	33.4	-21.0	-17.1
Base case – NCF	47.8	52.1	--	--
Increase credit	57.9	66.1	21.2	26.9
Increase NCF	51.4	55.2	7.7	6.0
Increase both	61.2	68.9	28.1	32.2
Increase obligation	40.3	45.0	-15.6	-13.6

Doubling EB from current levels also has a substantial impact on the probability of choosing a Navy option, though it is smaller than the impact of offering more credit. In contrast to offering more credit, increasing EB has about the same effect in both the submarine and the engineering scenarios because, according to our data, the utility of money increases at a decreasing rate. In other words, the change in utility associated with increasing the bonus for joining as a submarine technician from $10,000 to $20,000 is about the same as the change in utility associated with increasing the bonus for joining as an engineering technician from $12,000 to $25,000.

Because NCF values are greater than EB values, the fact that the value of money increases at a decreasing rate also means that the impact of increasing NCF by $10,000 is smaller than the effect of increasing EB by similar or even smaller amounts. Reporting changes in percentage terms magnifies this effect because the base case probabilities are larger for the NCF scenarios. Finally, increasing obligation lengths by one year in all three enlistment packages *decreases* the probability of choosing a Navy option by roughly the same amount that doubling EB *increases* it, and the impact of increasing obligation lengths is substantially larger in magnitude than that of increasing NCF.

Next, we directly translate the percentage changes in the probability of picking a Navy option into percentage changes in the share of the population that has high propensity. To do this, we associated the share of survey respondents that were classified as highly propended with the simulation base case and then applied the percentage changes reported in table 9. The result is predicted increases in the relative size of the high-propensity group that range from 1 to 4 percentage points and predicted decreases of 1 or 2 percentage points. Figure 15 shows these differences in propensity.[31]

Figure 15. Predicted changes in overall share of population that has high propensity



How can these predicted changes in propensity be translated into changes in actual numbers of new contracts? Because our definition of high propensity corresponds to the YATS definition of positive propensity, CNRC can take these notional changes in propensity and use them as inputs into the Enlisted Goaling Model to estimate the change in net new contracts associated with each of the simulated changes in enlistment offerings.[32]

In general, these results are consistent with conclusions drawn from the simulations that did not include "none." Specifically, long obligation lengths are an important factor that keeps young people away from the Navy, and offering college credit may be the most cost-effective way to draw in new recruits. An additional advantage of using credit as an incentive to get lower propensity recruits is that it does not require the Navy to increase financial incentives as much for high-propensity recruits who would have joined anyway.

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[31] See appendix E for a fuller discussion of the relationship between enlistment propensity and predicted changes in the probability of choosing a Navy option.

[32] CNRC uses the Enlisted Goaling Model to predict the number of net new contracts for each recruiting district as a function of relevant variables, such as the number of recruiters, advertising expenditures, civilian unemployment rates, and propensity for military service.

FINDINGS

Overall, the survey data yield interesting information about young people's preferences for the different components of an enlistment package. Combined with demographic data and self-reported enlistment propensities, the survey data also give some indications about how these different components can be used to attract different kinds of recruits.

DETERMINANTS OF ENLISTMENT PROPENSITY

In addition to confirming that certain demographic characteristics are strong determinants of enlistment propensity (e.g., gender and race), the data collected here indicated that enlistment propensity is also related to students' perceptions of their civilian-sector prospects:

- Medium-propensity respondents do better in high school
- Medium-propensity respondents are about 70 percent less likely than high-propensity respondents to be planning to enter the labor force directly after high school graduation.

ENLISTMENT BONUS VS. NAVY COLLEGE FUND

Analysis of the survey data yielded the following results when comparing preferences for enlistment bonuses relative to preferences for the Navy College Fund:

- NCF is more than twice as popular as EB of the same actuarial cost to the Navy.
- NCF is relatively more effective for medium-propensity youth than for high-propensity youth.

Together, these results suggest that NCF can be a cost-effective tool for expanding the recruiting market. However, there is a separate issue of retention later in a sailor's career that should affect policy-makers' decisions regarding EB versus NCF—specifically, how much does NCF act as a separation incentive for Sailors making their first- and second-term reenlistment decisions?

LENGTH OF OBLIGATION

Simulated preferences for different obligation lengths, holding other elements constant, showed the following:

- The EB equivalent cost of a 5-year commitment is 1.6 times that of a 4-year commitment, and the EB cost of a 6-year commitment is 2.7 times that of a 4-year commitment.
- Increasing obligation lengths decreases enlistment preferences more for medium-propensity respondents than for high-propensity respondents.

NAVY JOB

The survey data gave information on which occupations are relatively more popular. Given these preferences, the simulations showed how incentives can be used to direct recruits into occupations, or ratings, for which manpower needs are greatest. The results showed:

- Large bonuses are required to attract new recruits into submarine ratings.
- It takes larger bonuses to shift high-propensity than medium-propensity recruits away from the occupations of their choice.

The first result supports existing policy, while the second highlights the importance of giving choice of occupation to recruits who meet the high-propensity profile.

COLLEGE CREDIT

Simulations on college credit asked the question, "How much is one semester of credit worth?" The results of the simulation indicated that the amount varies with the amount of credit. Specifically, the simulations showed:

- The EB equivalent value of one or two semesters is about $2,000 per semester.
- The EB equivalent value of a third or fourth semester is about $5,000 per semester.

ENLISTMENT PROPENSITIES

Using predictions of the likelihood of picking a Navy option rather than the "none" option, we simulated the effects of different policy options on enlistment propensities. We found that:

- Offering appropriate amounts of college credit for Navy training in different programs had a large positive effect on propensity—about 3 percentage points.
- Increasing obligation lengths by just one year had a substantial negative effect on propensity—about 2 percentage points.

CONCLUSIONS

Operational market research using the CBC methodology expands our overall understanding of the recruiting market by providing new information about potential recruits' preferences for the different components of an enlistment package. The data show that respondents with different enlistment propensities have different preferences for the various incentives in the survey. One way to interpret these results is that they suggest there is a need for variable packages that can be targeted to different market segments. However, budgetary considerations and current recruiting difficulties may force the Navy to focus relatively more attention on incentives that have the potential of *expanding* the recruiting market.

For the Navy to expand its recruiting market, it will have to focus more efforts on attracting medium-propensity youth. The results of this study indicate that medium-propensity youth are more likely to favor the path of some college before working. Thus, CNRC must investigate ways to make serving in the Navy competitive with the alternative path of attending college and seeking employment in the private sector after having spent some time in college. More specifically, focusing on college-related incentives—NCF and college credit for Navy training—is likely to be an especially effective means by which to bring in more medium-propensity recruits without spending extra funds on high-propensity recruits who are already entering under existing incentive programs.

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Issues for Further Study

We recommend that the Navy pursue this methodology for studying recruitment incentives by building on the results of and the lessons learned from this study. More specifically:

- The Navy can use these study results to assess the relative values of NCF, EB, length of obligation, and college credit as recruiting tools. It is important to recognize, however, that these results represent averages across the sample, whereas any given potential recruit may value any one of the recruitment incentives most. Therefore, effectively expanding the recruiting market will require CNRC to continue offering a mix of incentive choices to prospective recruits.

- The Navy can use these study results as part of its larger-scale cost-benefit analyses. Existing cost-benefit analyses already do a good job of using continuation behavior to develop estimates of the benefits of recruits who enter the Navy with various incentives (e.g., recruits with longer lengths of obligation may have higher overall career continuation, or recruits with NCF may be more likely to leave the Navy after one enlistment term). What the current results do is help the Navy evaluate the effect of incentives on propensity, which CNRC can translate into an effect on the number of new recruits.

- The Navy should investigate ways to make serving in the Navy competitive with the alternative path of attending college and seeking employment in the private sector after having spent some time in college. For the Navy to expand its recruiting market, it must reach past the high-propensity youth to medium-propensity youth, who are more likely to favor the path of some college before working. In general, the results of this study and others indicate that, in the current economic environment, the way to attract more recruits is to turn the Navy into the "employer of choice," and, to do so, the Navy must find ways to appeal to a larger segment of the recruiting market.

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APPENDIX A: DEMOGRAPHIC SURVEY QUESTIONS

Before the conjoint portion of the survey:

Q1. How old are you?

Q2. Male or female?

Q3. What is your race/ethnicity?

Q4. How likely are you to serve in the Navy within the next two or three years?

Q5a. What is your current educational status—high school student, high school graduate, did not complete high school?

Q5b. If you are a high school student, what is your high school class this year—freshman, sophomore, junior, or senior?

Q5c. If you are a high school student, what do you plan to do after high school—attend 2-year college, attend 4-year college, or enter the workforce?

Q5d. If you are a high school graduate, what is your current status—attending 2-year college, attending 4-year college, working, or looking for work?

Q6. What were your grades in high school—mostly A's, mostly A's and B's, mostly B's, or mostly less than B's?

Q7. Do you have a computer at home?

After the conjoint portion of the survey:

Q8. How likely are you to serve in the Navy within the next two or three years?

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APPENDIX B: LOGIT OUTPUT—FULL SAMPLE, NO-PROPENSITY GROUP, HIGH-PROPENSITY GROUP

Tables 10 through 12 show the logit output for estimations using the full sample, the high-propensity group, and the no-propensity group. Estimation output for the medium-propensity group is presented in table 7 in the main text.

Table 10. Logit output for the model estimated using the full sample

	Attribute-level	Effect (std. dev.)
	Rating	
1	Electronics	-0.0038 (0.03017)
2	Computer	0.2576 (0.02848) ***
3	Engineering	0.1030 (0.02944) ***
4	Submarine	-0.4689 (0.03436) ***
5	Aviation	0.1121 (0.0318) ***
	Length of obligation	
6	4 years	0.5872 (0.02348) ***
7	5 years	0.2568 (0.02497) ***
8	6 years	-0.1286 (0.02738) ***
9	8 years	-0.7154 (0.03276) ***
	Incentive	
10	$5K EB	-0.5765 (0.05356) ***
11	$10K EB	-0.2698 (0.04815) ***
12	$20K EB	0.0450 (0.04376)
13	$30K EB	0.3184 (0.04095) ***
14	$30K NCF	0.0476 (0.04371)
15	$50K NCF	0.3810 (0.04033) ***
16	$70K EB	0.6550 (0.03809) ***
17	$10K EB & $40K NCF	0.5125 (0.03934) ***
18	No incentive	-1.1132 (0.06589) ***
	College credit	
19	<1 semester	-0.3914 (0.03370) ***
20	1 semester	-0.1700 (0.03160) ***
21	2 semesters	-0.0169 (0.03040)
22	3 semesters	0.1939 (0.02889) ***
23	4 semesters	0.3844 (0.02953) ***
24	None	1.1726 (0.02251) ***

Notes: 1. There are files built for 500 respondents and data for 10,000 choice tasks.
2. $\chi^2 = 4515.38820$.
3. *** indicates significance at the .01 level.

Table 11. Logit output for the model estimated using the high-propensity sub-sample

	Attribute-level	Effect (std. dev.)
	Rating	
1	Electronics	0.1293 (0.08890)
2	Computer	0.4484 (0.08562)***
3	Engineering	-0.0319 (0.09204)
4	Submarine	-0.5734 (0.10440)***
5	Aviation	0.0277 (0.09826)
	Length of obligation	
6	4 years	0.3450 (0.07336)***
7	5 years	0.2386 (0.07471)***
8	6 years	-0.1191 (0.07934)
9	8 years	-0.4645 (0.08666)***
	Incentive	
10	$5K EB	-0.6028 (0.15803)***
11	$10K EB	-0.2335 (0.14249)
12	$20K EB	-0.1582 (0.13676)
13	$30K EB	0.4722 (0.12391)***
14	$30K NCF	0.0354 (0.13316)
15	$50K NCF	0.4199 (0.12450)***
16	$70K EB	0.8410 (0.12059)***
17	$10K EB & $40K NCF	0.6198 (0.12347)***
18	No incentive	-1.3938 (0.20730)***
	College credit	
19	<1 semester	-0.4245 (0.10064)***
20	1 semester	-0.1808 (0.09519)
21	2 semesters	0.0447 (0.09090)
22	3 semesters	0.1686 (0.08835)
23	4 semesters	0.3920 (0.09115)***
24	None	-0.0527 (0.09056)

Notes: 1. There are files built for 41 respondents and data for 820 choice tasks.
2. $\chi^2 = 287.70582$.
3. *** indicates significance at the .01 level.

Table 12. Logit output for the model estimated using the no-propensity sub-sample

	Attribute-level	Effect (std. dev.)
	Rating	
1	Electronics	-0.0024 (0.05500)
2	Computer	0.2043 (0.05220)***
3	Engineering	0.0972 (0.05356)
4	Submarine	-0.3742 (0.06158)***
5	Aviation	0.0751 (0.05877)
	Length of obligation	
6	4 years	0.6789 (0.04284)***
7	5 years	0.2985 (0.04633)***
8	6 years	-0.1732 (0.05264)***
9	8 years	-0.8042 (0.06488)***
	Incentive	
10	$5K EB	-0.5159 (0.09836)***
11	$10K EB	-0.2960 (0.08988)***
12	$20K EB	-0.0169 (0.08226)
13	$30K EB	0.2945 (0.07462)***
14	$30K NCF	0.1604 (0.07722)**
15	$50K NCF	0.3580 (0.07328)***
16	$70K EB	0.6526 (0.06744)***
17	$10K EB & $40K NCF	0.4974 (0.07062)***
18	No incentive	-1.1343 (0.12753)***
	College credit	
19	<1 semester	-0.4245 (0.06333)***
20	1 semester	-0.1691 (0.05838)***
21	2 semesters	0.0511 (0.05473)
22	3 semesters	0.1497 (0.05331)***
23	4 semesters	0.3927 (0.05305)***
24	None	1.9369 (0.03843)***

Notes: 1. There are files built for 210 respondents and data for 4,200 choice tasks.
2. $\chi^2 = 3577.93723$.
3. ** indicates significance at the .05 level.
4. *** indicates significance at the .01 level.

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APPENDIX C: ATTRIBUTE IMPORTANCES—MEASUREMENT ISSUES

There are two fundamental issues with the measure of attribute importances used in this study. First, from the intuition behind the calculation, it's not hard to see that attributes with more levels might tend to have greater measured importance than those with fewer levels because they will have greater utility ranges. The phenomenon has been dubbed the "Number-of-Levels Effect,"[33] and this tendency does indeed show up in the data. In this study, the fact that the incentive attribute has nine levels, while the others have only four or five, means that the importance of incentive relative to the other attributes may be overstated.

The second issue is an aggregation issue that exists because of respondent heterogeneity. Because respondents may have very different preferences, it is theoretically best to calculate importances for each person and then average across the sample, rather than to calculate them using the average utilities generated by the logit model. For example, suppose the market being studied is dominated by two brands and that consumers in this market are typically strongly loyal to one brand or the other. Table 13 shows what the utilities for the attribute's brand and price might look like for this market. In this case, because half the respondents strongly prefer Brand A and the other half strongly prefer Brand B, the *sample-wide* average utilities for the two brands are tied at 25. Thus, because the importance of a given attribute depends on the difference between the maximum and minimum utility values associated with each of its levels, the importance of brand in this example appears to be zero. However, if we calculate the brand importances for each group first and then average them, we calculate that brand and price are almost equally important.[34]

Table 13. Hypothetical utilities and attribute importances in a market dominated by two brands

	Utilities		
Attribute	Group 1	Group 2	Average
Brand			
Brand A	0	50	25
Brand B	50	0	25
Brand range	50	50	0
Price			
$1	100	100	100
$2	40	40	40
Price range	60	60	60
Brand importance	45%	45%	0%
Price importance	55%	55%	100%

33 Wittink, Huber, Zandan, and Johnson, 1992.
34 Sawtooth Software, Inc., *CBC User Manual, Version 2.0,* pp. D4 and D5.

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APPENDIX D: DESIGNING AND INTERPRETING CBC SIMULATIONS

Although conventional wisdom in the field of CBC analysis says that a "none" choice should be included in all surveys to better model the consumer's option not to buy, there is some disagreement in the literature over how and whether choices of "none" should be used in the analysis of conjoint results.[35] The "none" choice was initially introduced into conjoint surveys for two reasons. First, as mentioned above, it is considered a more realistic way to model the choices that consumers (or potential recruits) actually make in the market place. Second, the hope was that the rate at which respondents picked "none" (or one minus that rate) could be used to estimate market shares (or likelihood of enlistment). Unfortunately, estimated probabilities of choice for the "none" option turned out to be bad predictors of market share in actual practice. The reasons for this are as follows:

- The real world of choices is very complex.
    - It's difficult to capture the whole market in a conjoint survey's choices.
    - It's virtually impossible to take into account external factors like product availability and marketing and sales efforts.

- Respondent behavior cannot be perfectly controlled.
    - Respondents don't pick "none" often enough because they think that by doing so they're being uncooperative.
    - Respondents pick "none" too often because they remember that the choices shown in the current task are not as good as some choices shown in previous tasks.

The first set of reasons is particularly relevant to this study because we did not include any non-Navy jobs in the survey, the range of naval occupations in the survey was not complete, and Navy manpower requirements are more likely to dictate rating assignment than is so-called consumer choice.[36]

Thus, given that CBC simulations assume that *all* relevant attributes influencing market share have been measured, CBC simulation output must be interpreted with care: probabilities of choice should be interpreted as relative indications of preference; they should *not* be interpreted as predictions of market share.[37] More specifically, analysis of simulation results should focus on the relative sizes of probabilities of choice rather than on the absolute values. For example, consider a simulation with two concepts for which the predicted probabilities of choice are 30 percent and 70 percent. The relevant conclusion to draw from these results is that, all else equal,

[35] Johnson, 1997.

[36] New developments in Sawthooth's CBC survey software will allow future survey designs that can more realistically model the choices between military service, private sector employment, and college.

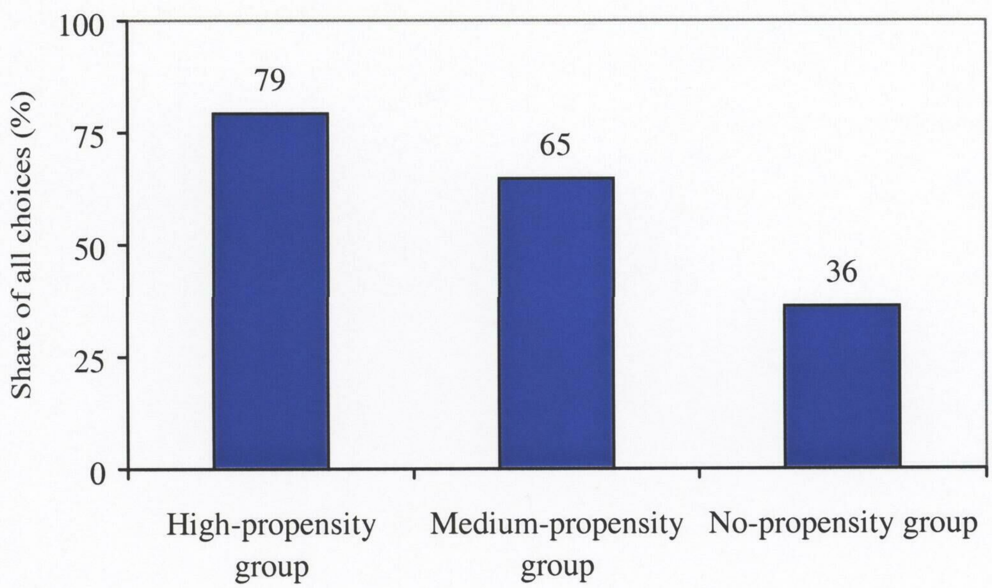
[37] Sawtooth Software, Inc., *Client Conjoint Simulator (CCS)*, pp. 2-1 and 2-2.

respondents are more than twice as likely to choose the second product as they are to choose the first. The results do *not* indicate that the first product will have a market share of 30 percent and the second a market share of 70 percent. In the context of this study, we should not interpret our predicted probabilities of choice as the percentage that would enlist. Rather, they more closely parallel the percentage of respondents who say they might enlist (i.e., propensity).

Appendix E: CBC simulation results and predicted changes in enlistment propensity

The justification for making the connection between the probability of picking a Navy option and enlistment propensity is that the rate at which respondents picked a Navy option rather than "none" on the survey tasks is directly related to their stated propensities. The data in figure 16 show the rates at which respondents in each propensity group picked a Navy option on the survey tasks (equal to one minus the rate at which they picked none). The data show that respondents in the high-propensity group picked a Navy option 22 percent more frequently than did respondents in the medium-propensity group and 119 percent more frequently than did respondents in the no-propensity group. Based on these relationships, we adopted the assumption that changes in the predicted likelihood of picking a Navy option could be mapped to predicted changes in enlistment propensities.

Figure 16. Percentage of survey tasks on which a Navy option was chosen by propensity group



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