UNR Joint Economics Working Paper Series
Working Paper No. 07-004

Patience Versus Decisiveness in Decision-Making

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August, 2007

Abstract

When rationality is bounded, a variety of factors may influence how far a choice is from optimal. We examine the willingness to search among alternatives. We find fixed individual differences in this temperament measure. People may be usefully typed according to how they obtain improved choices. More patient subjects obtain improvement by effectively using decision resources, performing better when the decision is more complex. More decisive subjects obtain improvement by conserving valuable decision resources, performing better when the decision problem is simple. We find that a bonus incentive frame encourages patience, while a penalty frame encourages decisiveness. These results suggest an organization can enhance its performance by matching individual temperaments and incentive frames to decision tasks at hand.

JEL Classification: D01, D81, D83

Keywords: framing, deliberation cost, bounded rationality, heuristics, incentives

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When rationality is bounded, a variety of factors may influence how far a choice is from optimal. We examine the willingness to search among alternatives. We find fixed individual differences in this temperament measure. People may be usefully typed according to how they obtain improved choices. More patient subjects obtain improvement by effectively using decision resources, performing better when the decision is more complex. More decisive subjects obtain improvement by conserving valuable decision resources, performing better when the decision problem is simple. We find that a bonus incentive frame encourages patience, while a penalty frame encourages decisiveness. These results suggest an organization can enhance its performance by matching individual temperaments and incentive frames to decision tasks at hand.

* The authors thank John Conlisk, Daniel Parent and Jesse Rothstein for helpful comments and suggestions. The authors also thank the University of Nevada and NSF Grant SBR-9709333 for supporting this research.

1. Introduction

In his *Nichomachean Ethics,* Aristotle associates vice with extreme behavior, excess on one end and deficiency on the other; virtue is a balance somewhere between these extremes. Here, we seek understanding as to where virtue lies between patience and impatience in the typical decision process, or equivalently, between decisiveness and indecisiveness. Decisiveness (or impatience) has virtue because it conserves decision resources, but patience (or indecisiveness) also has virtue because it protects against accepting a poor alternative as a choice.

Limited cognitive capacity bounds rationality (Simon, 1955), implying a deliberation cost arises as alternatives are considered (e.g., a foregone use of time). Yet, it is common to abstract from deliberation cost, explicitly or implicitly assuming it to be zero. In this unboundedly rational world, an optimal choice is made a set of alternatives, by assumption. “Choice” in this world is the optimal response to the environment, and choice theory involves mapping optimal responses to environmental conditions. This standard approach can fruitfully be used to predict how changes in a decision environment would be expected to affect the actions of a decision maker.

Recognizing deliberation cost complicates the analysis because the choice no longer depends only upon the location of the optimum. The boundedly rational decision maker must seek a quality choice while simultaneously managing deliberation cost, so the decision process will also tend to affect the location of the choice. A benefit from recognizing deliberation cost is that standard choice theory can be extended behaviorally (Pingle, 2006). A variety of behaviors can be explained as ways people cope with deliberation cost. For the present purpose, some factors can as influence choice (i.e., patience/decisiveness), even though they may not affect the location of the optimal choice.[1]

It is tempting to think one can “fold in” deliberation cost and construct a second order optimization problem, so the decision-maker simultaneously decides both how to decide and what to decide. We can learn by doing this (e.g., Baumol and Quandt (1964)). However, an “infinite regress problem” arises because the second order problem must also be costly to solve (Conlisk

[1] Kagan (1994), for example, explains why temperament can affect labor market outcomes. More directly related to our study, Damasio (1995) reports instances where brain injuries did not significantly change scholastic test scores, but had profound negative consequences for labor market performance because of increased indecisiveness. He gives an example of a patient who spent half an hour discussing contingencies that might make it difficult to schedule a meeting on a particular day.

(1988, 1995), MacLeod (2002)). Gigerenzer and Selton (2001, p.5) argue it is "inappropriate and misleading" to interpret bounded rationality as "a hidden form of optimization." They rather perceive it as the application of an "adaptive toolbox" of "fast and frugal" heuristics. A heuristic is effective, not because it is an optimization algorithm, but because it fits a particular decision environment (Gigerenzer and Selton, 2001, p.9), simultaneously economizing on decision resources and yielding a high quality choice. This perspective suggests individual non-cognitive characteristics like patience/decisiveness may influence choice by influencing the heuristic the decision maker applies in a given context.

Because the infinite regress problem limits the ability to derive theories of bounded rationality from the optimization assumption, experimentation is especially advantageous. It allows us to empirically examine how people cope with deliberation cost. Few experimental studies have examined decision behavior with deliberation cost, however. An interesting exception is the "real effort experiment" of van Dijk, Sonnemans, and van Winden (2001). They examine the impact of various incentive schemes on the decision effort put forth human subjects, measured as the number of costly steps taken in search of the optimum.[2] Our study is comparable in that we present human subjects with a series of optimization problems, and a subject must search through alternatives sequentially to arrive at a choice.[3] In considering whether to stop or continue the search, the decision maker faces a trade-off: Conserve valuable decision resources or seek an improved decision, hoping the improvement will more than compensate for the decision resources used.[4] We view this as a ubiquitous decision problem, and one that is not fully understood.

We deviate from van Dijk, Sonnemans, and van Winden by providing our subjects with more flexibility as to how they search. We do not require subjects to start their search at a particular location, nor do we require successive trials to be adjacent. On a given trial, our subjects are free to sample an alternative from anywhere in the search space. While this weakening of experimental control increases the number of potential confounds, it is essential because we want to

[2] Their primary finding was that tournament prizes induced a higher but more variable level of effort than piece rate pay or team remuneration, which did translate into improved decision performance.
[3] Simon (1955) argued that most real world decision making would involve the sequential comparison of alternatives because people have limited cognitive capacity. This is consistent with theory on optimum seeking methods in mathematics (see Cooper and Steinberg (1970) and Wilde (1964)), where sequential search is generally recognized as being preferable to the simultaneous comparison of a number of alternatives because the information obtained from one trial in sequential search can be used strategically to select the location of the next trial.
[4] Payne, Bettman, and Johnson (1988) label this the "effort-accuracy" tradeoff, and they explore the processes by which people cope with it.

consider how various factors interact. By adopting this approach, we partially address the criticism that experimental environments can be so simplified that the results obtained from them will tend to be irrelevant. [5] Further, our approach allows us to measure interactions and distinguish the relative impacts of various factors using econometric techniques.

Nonetheless, we take advantage of experimental control. We control for "aspiration uncertainty" by constructing optimization problems so the value of the objective function at the optimum is the same for each problem, and subjects are informed of this optimal value.[6] We also control for the self-selection problems that are typically present in field situations by confronting all subjects with the same set of varied problems.[7]

List and Harrison (2004) note that no matter how much experimental control is applied, human subjects bring differing experiences to experiments that may influence their behavior. Rather than try to control away all such differences through experimental design, we estimate fixed individual differences using the panel data from our experiment, and we distinguish the impacts of individual differences from the characteristics of the problem. Gigerenzer (2001) indicates fixed individual differences in decision behavior may occur because subjects possess different heuristics in their adaptive tool boxes. Our primary interest is in whether there are fixed individual differences in patience/decisiveness, measured as the willingness to expend decision resources in costly search. We use subject demographic data to gain insight about the origins of the unobservable fixed differences we estimate. We also explore the extent to which fixed differences in patience/decisiveness help explain differences in total decision performance for problems of varying complexity.[8]

Like van Dijk, Sonnemans, and van Winden (2001), we introduce treatments into our experiment to examine different incentives. However, we start at a more fundamental level of analysis by examining the incentive frame. Our incentive question is, "Controlling for other significant factors, can a change from a bonus to a penalty frame influence the quality of the decision, the willingness to search, or both?" Lazear (1995, pp. 65-69) notes why the prospect theory of Tversky and Kahneman (1979, 1981, 1991) might explain a framing effect. If a subject

[5] See Falk and Fehr (2003) for a discussion of this criticism and the use of experimental methods in labor economics.
[6] MacLeod and Pingle (2005) illustrate how a discrete change in the level of aspiration uncertainty can affect decision behavior.
[7] See Angrist and Krueger (1999) for a discussion of various techniques that have been used in labor economics to address this self-selection problem.
[8] Harrison and Morgan (1990) explore the extent to which individuals use different search strategies, but do not ask the extent to which performance is specific to the individual.

perceives the given wage as the "status quo" and is "loss averse," then a penalty for not performing as well as possible should be more motivational than a bonus received for improvement. So, a penalty frame should generate more patience in search, more decision resource use, and higher quality choices. A competing alternative hypothesis is that the "positive reinforcement" of the bonus frame may motivate more search than the "negative reinforcement" of the penalty frame.[9]

The paper is organized as follows. Section 2 presents the experimental design. Section 3 discusses the data obtained from the experiment and defines variables. Section 4 presents detailed results. Section 5 concludes with a summary of the results and some discussion.

2 The Experiment

The experiment involves examining the behavior of human subjects as they solve a series of optimization problems, presented as an "effort allocation game." (See the Appendix for sample game instructions.) For a given problem, 200 units of "effort" are allocated to varying "tasks." The dimensionality of the optimization problem increases with the number of tasks, which makes the problem more complex. The most simple problem involves allocating effort to only two tasks, while the most complex involves an allocation to five tasks.

The quality of an allocation $(y_1, y_2, y_3, y_4, y_5)$ is measured in "search points" S, where

$$S = \alpha_1 y_1 + \alpha_2 y_2 + \alpha_3 y_3 + \alpha_4 y_4 + \alpha_5 y_5 - \left[\beta_1 y_1^2 + \beta_2 y_2^2 + \beta_3 y_3^2 + \beta_4 y_4^2 + \beta_5 y_5^2\right] - f \ .$$

The parameters f, α_i and β_i are chosen so the maximum value for S, S_{opt}, is 50 for each problem, given the constraint $y_1 + y_2 + y_3 + y_4 + y_5 = 200$. (Of course, α_i and β_i are set equal to zero for $i > k$ for problems with $k < 5$ tasks.) The subject is never shown this objective function, so

[9] In psychology, reinforcement is defined to be a consequence that causes a targeted behavior to be more likely. Positive reinforcement motivates by introducing an attractive stimulus, which is called a "positive reinforcer," subsequent to the targeted behavior. "Negative reinforcement" motivates by removing an unattractive stimulus, which is called a "negative reinforcer," subsequent to the targeted behavior. Psychologists still dispute whether positive reinforcers are more effective motivators than negative reinforcers. Heron (1987, p. 257) describes positive reinforcement as "the most widely applied principle of behavior," having been successfully applied "in numerous training and development programs across a wide variety of populations, settings, and behaviors." Wiegand and Geller (2005) critique the use of "failure avoiding" negative reinforcers and extol "success-seeking" positive reinforcers. Alternatively, in is his provocative article, "What organizational behavioral analysis needs is more Jewish mothers," Malott (2002) argues that the fear of failure, or fear of not living up to high expectations, is a powerfully motivating negative reinforcer that is underappreciated.

there is no opportunity to formulate and solve a mathematical optimization problem. Rather, the subject must seek the optimum by engaging in sequential search.

Search is costly. For a given problem, the subject's "efficiency bonus" is $EFF = \gamma_1[375 - ALT1*15]^{\gamma_2}$, which decreases as the number trial alternatives ALT1 increases. At one extreme, if the subject accepts the first trial as the choice, the maximum efficiency bonus of 49.1 points is earned. At the other extreme, the efficiency bonus equals zero and the game automatically terminates after the subject's 25th trial. Because we are examining the willingness to search, we prefer that the subject choose to stop the search, rather than being censored. A pilot experiment indicated that a very slight increase in the marginal cost of search encourages most subjects in this experimental setting to stop their search before reaching trial 25. Setting the parameters γ_1 and γ_2 equal to 0.33 and 0.85 provides this slightly increasing marginal cost. With this design, a small amount of censoring did occur, but very little.

After entering a trial alternative, the subject has a maximum of 15 seconds to decide whether or not to continue the search. Waiting longer than 15 seconds reduces the efficiency bonus, just as when an additional trial is actually used. As long as a subject uses less than 15 seconds to enter a trial, the cost of search depends upon the number of trials, not time used. This design feature serves two purposes. First, it prevents differences in the ability to enter computer keystrokes from affecting the results, for 15 seconds is long enough for those less experienced with a keyboard to make an entry. Second, it prevents a subject from being able to think without cost.

The experiment's single treatment is the frame of the incentive: bonus versus penalty. In the bonus group, a small fixed wage is paid, and a "decision bonus" increases to a maximum as the quality of the decision increases. In the penalty group, a large fixed wage is paid, and a "decision penalty" decreases to a minimum as the quality of the decision increased.

The "decision bonus" for the bonus group is $S_{\max}$, the number of search points associated with the best of all the trial alternatives. The "decision penalty" for a decision in the penalty group decision is $S_{opt} - S_{\max}$. The only difference between the two groups is the frame of the incentive in that "total earnings" is the same when decision behavior is the same:

$$
\begin{aligned}
\text{Bonus Group Total Earnings} &= \text{Bonus Group Wage} + \text{Decision Bonus} + \text{Efficiency Bonus} \\
&= 1 + \mathrm{S_{max}} + \mathrm{EFF} \\
&= \left[1 + \mathrm{S_{opt}}\right] - \left[S_{opt} - S_{\max}\right] + \mathrm{EFF} \\
&= \text{Penalty Group Wage - Decision Penalty} + \text{Efficiency Bonus} \\
&= \text{Penalty Group Total Earnings}
\end{aligned}
$$

Figure 1 displays the game screen and a sample entry for a subject in the bonus group. This is the fourth game played by the subject. The problem is the most complex 5 task type. The second trial allocation, or search opportunity, is being considered. The subject is allocating 45 units of effort to tasks 1, 2, 3, and 4 on this trial. The computer has entered the balance of 20 units of effort to task 5. (For all games, the computer enters the allocation for the final task in this manner so that variation in decision performance does not occur because of variation in adding errors.)

Figure 1: The Game Screen

Game 4
Game Type: 5 Tasks
Search Opportunity 2

	Best	Last	2 Back
Effort Level Y1: 45	45	34	0
Effort Level Y2: 45	45	34	0
Effort Level Y3: 45	45	34	0
Effort Level Y4: 45	45	34	0
Effort Level Y5: 20	20	64	0
Search Points: 7.4	7.4	-46.9	0

Continue Search
Stop Search

Wage:	1.0		
Decision Bonus:	7.4		
Efficiency Bonus:	47.4	Cost of Next Trial:	1.76
Total Earnings:	55.8		

The trial (45,45,45,45,20) generates 7.4 search points. The "Best" column indicates that this trial is the best trial made up through the current search opportunity. The "Last" and "2 back" provide a short term "memory." This design feature limits the extent to which decision performance varies because of differences in short term memory capabilities. In this example, the subject does not have to use memory to know that the previous trial (34,34,34,34,64) is worse than the current trial (45,45,45,45,20).

In this example, the best trial in the search process is the current trial, and total earnings would be 55.8 points if this trial is accepted as the choice. These earnings are the sum of the wage (1), the decision bonus (7.4), and the efficiency bonus (47.4). If a penalty group subject had made this same choice on the second search opportunity, then the total earnings would have been the same, but would have been calculated as 55.8=[1+50]-[50-7.4]+47.4, a wage of 51, a decision penalty of 42.6, and an efficiency bonus of 47.4.

At this point, the subject must decide whether to continue searching or not. There is no uncertainty about how much room there is for improvement in the quality of the choice. Subjects in the bonus group know the maximum decision bonus is 50, and subjects in the penalty group know the minimum penalty is zero. The subject is also shown the cost (in terms of lost efficiency bonus) of examining an additional trial alternative, so there is no uncertainty there. The uncertainty present in the choice lies in the subject's own subjective belief about his or her own ability to capture the improvement that is possible. To continue searching, the subject hits the enter key, and enters another trial allocation. To stop searching, the subject selects the stop search option and hits the enter key, upon which the computer records the results and immediately begins the next game.

After reading the game instructions, all participants in a session play a single, highly structured, tutorial game called the "administrative game." Subjects are not allowed to experiment with this game on their own, but rather are told what to do step by step. The administrative game ensures subjects understand what is presented on the computer screen and know how to navigate on the computer. Subjects then play four "practice games," to become exposed to each of the four game types.

Subjects then play the 20 games of the experiment. A 2 task problem was played, then a 3 task problem, 4 task problem, an 5 task problem. This pattern was repeated 4 times, allowing the effect of experience to be examined and controlled for. For each problem type, set of optimal choices each provided an optimal search point value of 50, but were placed in dispersed locations. A Euclidean distance measure was used to ensure that the dispersion of the optimal choices for each problem type was roughly equivalent.

Each subject was paid the cumulative earnings generated by the 20 choices, after completing a questionnaire. Subjects understood that the performance in one game, good or bad, does not affect the earnings opportunity in any future game, cumulative earnings was not shown during play. For the typical participation time of about one hour, the average earnings level was $13.70, ranging from $10.13 to $16.78. All were volunteer undergraduate students recruited from University of Nevada, Reno economics courses. A total of 52 subjects participated, 26 in the bonus group and 26 in the penalty group.

3. Data and Variables

SUBJECT is a categorical variable associated with the 52 participants. Variables describing individual subject characteristics are associated with SUBJECT, including GROUP (0=bonus frame, 1=penalty frame), SEX (1=male), MAJOR (1=business), MARRY (1=married), FINAID (1=receiving), AGE (age in years), GPA (GPA on University of Nevada credits), CRED (number of college level credits completed), and WORK (average hours worked for pay per week).

In addition to collecting demographic information, the questionnaire sought verbal descriptions of the subject's search process. Subjects were asked, "To the best of your ability, describe the method or methods you used when playing the effort allocation game." The other question was, "To the best of your ability, describe how you decided when to stop searching." Responses were varied but could be categorized according to whether a search method was used and according to the reported stopping rule. This categorization provided the variables SSRULE (1=report systematic search rule of some sort), CBRULE (1=report comparing costs of additional search to benefits), BRULE (1= report consideration of benefits of additional search, but no mention of costs), CRULE (1=report consideration of costs of additional search, but no mention of benefits).

Table 1 presents descriptive statistics on subject demographics and decision rules. Thirty-seven percent of subjects provide some indication of using a systematic search method, while most provide no such evidence. Only ten percent indicate that they compare the costs of additional search to the benefits. A disproportionate 73 percent report consideration of the potential benefits of additional search, but not the costs, while 17 percent report the converse.

The number of search opportunities used by the subject on a given choice problem, ALT1, ranges from 1 to 25. Variables associated with ALT1 describe the decision process, and include the number of search points S generated by opportunity ALT1, the number of search points SMAX generated by the best trial alternative through search opportunity ALT1, the efficiency bonus EFF obtained if search is stopped on search opportunity ALT1. FINAL is a dummy variable set equal to one when on the search opportunity when search stops, and set to zero otherwise. That is, FINAL=1 identifies the alternative trial that is the choice for the given decision problem.

Table 1: Subject Demographics and Decision Rules				
Subject Characteristic	Mean	Standard Deviation	Min	Max
Demographic				
AGE	23.00	4.30	18	39
GPA	3.00	0.77	0.61	4.00
CRED	82.10	47.70	3	179
WORK	13.70	13.40	0	55
SEX	0.62	0.49	0	1
MAJOR	0.71	0.46	0	1
MARRY	0.08	0.27	0	1
FINAID	0.40	0.50	0	1
Decision Rule				
SSRULE	0.37	0.49	0	1
CRULE	0.10	0.30	0	1
BRULE	0.73	0.45	0	1
CBRULE	0.17	0.38	0	1
Note: There were 52 observations (subjects) on the demographic and decision rule variables				

Other variables defined for the analysis include ROUND, the problem number running from 1 to 20; TASK, the problem type, or number of tasks present in the problem, running from 2 to 5; and EXP_i, a dummy variable set to one when the subject has $i = 1,2,3,4$ previous experiences with the given problem type. Other variables, constructed to examine results of interest, are identified and described below when the results are presented.

With 52 subjects making 20 choices each, the data set included 1040 observations on choices (where FINAL=1). Two outlier choices were removed in two cases where a subject unintentionally accepted a very poor choice (more than 4 standard deviations below the mean) even though many more search opportunities remained available. Consequently, the data set included observations 1038 choices.

4. Results

We model the degree of patience/decisiveness exhibited by a subject using a Cox proportional hazard model. The probability $\theta_i(t)$ that subject i stops searching on trial alternative t is given by $\theta_i(t) = e^{\beta x_{it}} \theta_i^0(t)$, where x_{it} is a vector of factors describing the subject's state on trial t, β is the set of parameters to be estimated, and $\theta_i^0(t)$ is the baseline hazard. The baseline hazard is non-parametric, capturing the time varying nature of the "standard" willingness to stop the search. When x_{it} includes person specific, time invariant characteristics, the baseline hazard $\theta_i^0(t)$ does not depend upon the subject i (analogous to a regression with no fixed effects). When all individual characteristics are time varying, the data can be stratified to estimate a person specific baseline hazard (analogous to a regression with fixed effects).

Table 2 presents the results obtained from five hazard model regressions. The "all tasks" regression uses data from all problem types, while the 2 task, 3 task, 4 task, and 5 task regressions use data only for the given problem type. Of the 1,038 problems solved by all subjects, search was censored or terminated by the computer (after 25 trials) on 29 occasions. We dropped these few censored choices from the hazard model regressions, for we seek understanding about why subjects choose to stop searching. For the all tasks regression, this meant 8,155 trial allocations from the remaining 1,009 choice problems were used to estimate the propensity to stop search.

The "hazard ratio" for each explanatory variable is reported.[10] When the explanatory variable is categorical, one category must be left out of the regression to obtain identification. In this case, the hazard ratio indicates the likelihood of stopping the search, relative to the category left out. For example, the TASK4 variable is left out, so the hazard ratio of 10.57 reported for the TASK2 variable in the all tasks regression indicates that the average subject is 10.57 times more likely to stop searching when solving a 2 task problem than a 4 task problem, controlling for the other factors. When the variable is not categorical, like the variables WORK and CRED, then a hazard ratio greater than one indicates a positive correlation between the variable and the probability of stopping the search, while a ratio less than one indicates a negative correlation.

[10] One, two, and three asterisks represent significance at the ten, five, and one percent levels of significance. Standard errors are not presented because they do not apply to the hazard ratios, but rather relate to the estimated coefficients for the factors.

Table 2: Hazard Ratios for the Dependent Variable ALT1

Variable	All tasks	2 tasks	3 tasks	4 tasks	5 tasks
GROUP	1.919***	1.216	2.05***	3.17***	1.807***
TASK2	10.57***				
TASK3	1.336***				
TASK5	0.761***				
SM10	3.168***	2.401***	2.736***	4.387***	3.251***
SM 20	1.976***	2.201***	1.502	3.131***	1.411
SM 30	1.430***	1.500*	0.907	2.357***	0.814
SM 40	1.065	0.999	1.172	1.239	0.762
SM 60	0.866	0.478**	0.569*	1.342	1.102
SM 70	0.504***	0.737	0.310***	0.592	0.349***
SM 80	0.387***	0.579	0.154***	0.542	0.362**
SM 90	0.324***	0.345***	0.331**	0.331**	0.455*
SM 100	0.125***	0.191***	0.124**	0.000***	0.260
EXP2	1.305***	0.894	1.408	1.586**	1.536*
EXP3	1.786***	1.400	0.779	1.530*	5.032***
EXP4	1.528***	0.689	0.950	3.285***	3.017***
EXP5	1.252**	0.956	0.883	1.384	0.850
CRULE	9.399***	4.779***	12.07***	29.15***	45.70***
BRULE	3.416***	1.130	6.008***	7.969***	10.53***
SSRULE	1.366***	1.229	1.210	1.516**	1.736***
GPA	1.303***		1.224**	2.24***	2.058***
SEX	1.259***			2.214***	2.419***
WORK	1.009***			1.027***	1.032***
CRED	0.995***	0.994***		0.992***	0.994***
FINAID	0.752***		0.398***	0.430***	0.707**
MARRY	0.736**				0.473***
MAJOR	1.839***		3.487***	3.261***	2.484***
ASIAN	0.566***	0.576***	0.318***		0.738*
Age			0.931***		
Total Trials	8155	708	2123	2518	2806
Problems	1009	260	258	252	239
Log Likelihood	-7318.3	-1444.0	-1504.9	-1504.5	-1445.2
LR	1548.9	175.1	276.4	320.7	365.6
LR p-value	0.000	0.000	0.000	0.000	0.000

Of primary interest here is the impact of the incentive frame on patience/decisiveness. In assessing this impact, we control for the complexity of the problem (using the TASK dummies), for experience (using the EXP dummies), for any reported decision methods (using CRULE, BRULE, and SSRULE), and for demographic characteristics (using the demographic variables presented in Table 1). Importantly, we also control for how near the given trial allocation is to the optimum (using the dummies sm10 to sm100). When sm10=1, the trial is among the nearest 10% of trials for the given problem type (e.g. 3 task problems). At the other extreme, sm100=1 implies the trial is among the 10% of trials furthest from optimal for the given problem type.

The marginal impacts of the control variables are, for the most part, as would be expected. The probability of stopping the search increases at an increasing rate as the subject nears the optimum. Reducing problem complexity increases the probability of stopping the search, as does experience (in general) and the use of a systematic search method (SSRULE=1). Subjects who reported using a stopping rule that focused only on the costs of search (CRULE=1) or only on the benefits (BRULE=1) tended to stop sooner than subjects who reported the consideration of both costs and benefits as they searched (left out variable CBRULE=1).

We ran "stratified sample" regressions to estimate individual baseline hazard ratios. These results are not reported because controlling for unobserved individual differences in this manner did not significantly alter the hazard ratios reported for the other variables. The regressions presented in Table 2 include the <u>observable</u> individual characteristics that significantly affect the willingness to stop the search. We found more decisiveness (less patience) is associated with a higher GPA, being male, working more hours per week, being a business major, having fewer accumulated college credits. Alternatively, more patience (less decisiveness) is associated with receiving financial aid, being married, and being Asian.

The very high hazard ratio for the 2 task problem in the "all tasks" regression indicates subjects especially economized on search in this most simple environment. The separate regressions by problem type help uncover some interactions between problem complexity and other factors. Those who reported using some kind of systematic search method (SSRULE=1) especially tended to stop their search sooner in the more complex 4 and 5 task problems, indicating that a benefit of using a systematic search method is being able to economize on decision costs when the search problem is more complex. Likewise, experience and differences in individual demographic characteristics tended to have more impact when the problem was more complex.

Controlling for the other factors, the penalty incentive frame increased the probability of stopping the search relative to the bonus frame. That is, we find that a penalty frame encourages decisiveness, while bonus frame encourages patience. The larger hazard ratios for the 3 and 4 task problems indicate that this framing effect is stronger when the problem is of intermediate complexity.

How do differences in patience/decisiveness affect decision performance? Decision performance is measured by the TOTAL earnings, which is equal SMAX+EFF+1. A larger value for EFF indicates less use of decision resources, so it is also and indication of more decisiveness (less patience). A larger value for SMAX indicates higher decision quality. The size of SMAX relative to EFF provides an indication of "composition" of total decision performance. Table 3 presents means, standard deviations, and coefficients of variation for TOTAL, SMAX, and EFF by problem type and by incentive frame.

Table 3: Decision Performance by Problem Complexity and by Incentive Frame (Means, Standard Deviations, Coefficients of Variation)

	Treatment	2 tasks	3 tasks	4 tasks	5 tasks
Mean Performance (n=130)					
TOTAL	Bonus	94.9	73.3	63.2	48.6
	Penalty	94.8	74.1	62.3	48.2
SMAX	Bonus	48.1	36.7	30.6*	18.2
	Penalty	47.4	36.7	26.8*	15.3
EFF	Bonus	45.8	35.6	31.6*	29.4
	Penalty	46.3	36.5	34.5*	31.9
Performance Standard Deviation (n=130)					
TOTAL	Bonus	6.2	19.5	23.2	35.5
	Penalty	5.7	17.3	22.5	35.2
SMAX	Bonus	3.8	17.1**	16.4	27.9
	Penalty	3.6	13.8**	18.6	31.1
EFF	Bonus	5.1**	10.2	13.9***	15.1**
	Penalty	4.2**	9.9	10.2***	12.4**
Coefficient of Variation (n=130)					
TOTAL	Bonus	0.065	0.266	0.367	0.730
	Penalty	0.060	0.233	0.361	0.730
SMAX	Bonus	0.079	0.466	0.536	1.533
	Penalty	0.076	0.376	0.694	2.033
EFF	Bonus	0.111	0.287	0.440	0.514
	Penalty	0.091	0.271	0.296	0.389

* Significant difference between the two treatments at 10% level of significance
** Significant difference between the two treatments at 5% level of significance
*** Significant difference between the two treatments at 1% level of significance

As would be expected, total decision performance decreases as problem complexity increases, and becomes more variable. More interestingly, we find that the share of overall performance attributable to decision quality decreases as complexity increases. For example, SMAX and EFF make roughly equal contributions to TOTAL earnings for the 2 task and 3 task problems, whereas EFF is about double SMAX for the 5 task problems.

Comparing the bonus and penalty incentive frames, there is no significant difference in overall performance at any problem complexity level. However, when we decompose total performance, consistent differences do arise. At each problem complexity level, subjects in the bonus group make higher quality choices (i.e., higher SMAX), while subjects in the penalty group economize more on the use of decision resources (i.e., higher EFF). These differences are more pronounced for the more complex problem types, and very significant for the 4 task problems. At all complexity levels, the use of decision resources varied more for bonus group subjects than penalty group subjects. Thus, we find that the bonus frame encourages the patient use of decision resources, while the penalty frame encourages decisiveness that conserves decision resources. Moving from a bonus frame to penalty frame reduces the variability in the degree of patience/decisiveness observed.

We are interested in whether fixed individual differences in patience decisiveness are exhibited. To estimate fixed differences, we model the decision performance of subjects as a function of the observable characteristics of the decision problem. After experimenting with different functional forms, we chose the relationship $1/(101 - TOTAL_{it}) = e^{\beta_{it} x_{it}} e^{f(s_t)} e^{\mu_i} e^{\varepsilon_{it}}$, which becomes $-\ln(101 - TOTAL_{it}) = \beta_{it} x_{it} + f(s_t) + \mu_i + \varepsilon_{it}$ after taking the natural log. $TOTAL_{it}$ is the decision performance of the individual i on problem t, which reaches a maximum for each problem at a value just under 100. Thus, $-\ln(101 - TOTAL_{it})$ is a measure of the distance from the optimum. The coefficients β_{it} are the estimated marginal effects of the factors x_{it}, which vary either by the problem t or by the individual i; s_t is the number of search points earned on the first trial choice (when ALT1=1) for problem t, and $f(s)$ is a general step function explained further below; μ_i is the individual fixed effect for individual i; and ε_{it} is a random error. The fact that this semi-log specification resulted in a better fit than linear specifications indicates that obtaining improved performance is more difficult to as the optimal choice is approached, regardless what factor is generating the improvement. An analogous functional form was applied to model decision quality SMAX and to model decision efficiency EFF. Table 4 presents the results of these regressions, with standard errors shown in parenthesis.

Table 4: Decision Performance Regressions

Variable	Total Performance			Decision Quality			Decision Efficiency		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Constant	-3.480	-3.544	-3.709	-2.795	-2.899	-2.483	-2.574	-2.606	-3.750
	(0.077)***	(0.072)***	(0.177)***	(0.109)***	(0.095)***	(0.142)***	(0.105)***	(0.087)***	(0.235)***
Group	-0.054		-0.062	-0.193		-0.241	0.058		0.156
	(0.038)		(0.038)	(0.054)***		(0.055)***	(0.052)		(0.054)***
task2	2.097	2.096	2.096	2.262	2.261	2.262	1.700	1.699	1.699
	(0.053)***	(0.051)***	(0.052)***	(0.075)***	(0.068)***	(0.073)***	(0.073)***	(0.062)***	(0.068)***
task3	0.395	0.394	0.394	0.637	0.634	0.637	0.218	0.217	0.216
	(0.053)***	(0.051)***	(0.052)***	(0.076)***	(0.068)***	(0.073)***	(0.073)***	(0.062)***	(0.068)***
task5	-0.261	-0.261	-0.261	-0.396	-0.400	-0.398	-0.126	-0.124	-0.124
	(0.053)***	(0.051)***	(0.052)***	(0.076)***	(0.068)***	(0.073)***	(0.073)*	(0.062)**	(0.068)*
luck10	1.154	1.228	1.168	0.998	1.003	1.013	1.219	1.329	1.223
	(0.085)***	(0.084)***	(0.083)***	(0.12)***	(0.111)***	(0.116)***	(0.116)***	(0.102)***	(0.109)***
luck20	0.486	0.517	0.506	0.550	0.512	0.566	0.359	0.498	0.390
	(0.084)***	(0.083)***	(0.083)***	(0.119)***	(0.111)***	(0.115)***	(0.115)***	(0.101)***	(0.108)***
luck30	0.321	0.356	0.331	0.232	0.262	0.275	0.239	0.276	0.218
	(0.085)***	(0.084)***	(0.084)***	(0.121)*	(0.111)**	(0.117)**	(0.116)**	(0.102)***	(0.109)**
luck40	0.102	0.175	0.146	0.127	0.206	0.179	-0.004	0.061	0.028
	(0.082)	(0.08)**	(0.081)*	(0.116)	(0.107)*	(0.112)	(0.112)	(0.097)	(0.105)
luck60	-0.177	-0.082	-0.137	-0.176	-0.076	-0.141	-0.151	-0.080	-0.131
	(0.084)**	(0.083)	(0.083)*	(0.12)	(0.111)	(0.115)	(0.115)	(0.101)	(0.109)
luck70	-0.254	-0.219	-0.238	-0.076	-0.116	-0.078	-0.296	-0.208	-0.294
	(0.083)***	(0.082)***	(0.082)***	(0.118)	(0.109)	(0.114)	(0.113)***	(0.099)**	(0.107)***
luck80	-0.347	-0.315	-0.329	-0.075	-0.157	-0.101	-0.402	-0.270	-0.353
	(0.084)***	(0.083)***	(0.083)***	(0.12)	(0.11)	(0.116)	(0.115)***	(0.101)***	(0.108)***
luck90	-0.576	-0.588	-0.568	-0.331	-0.387	-0.328	-0.684	-0.640	-0.665
	(0.084)***	(0.082)***	(0.083)***	(0.12)***	(0.11)***	(0.116)***	(0.115)***	(0.1)***	(0.108)***
luck100	-0.567	-0.552	-0.550	-0.362	-0.382	-0.364	-0.641	-0.603	-0.629
	(0.084)***	(0.084)***	(0.083)***	(0.12)***	(0.111)***	(0.116)***	(0.115)***	(0.102)***	(0.109)***
exp2	-0.006	-0.009	-0.007	-0.041	-0.025	-0.038	0.106	0.086	0.101
	(0.061)	(0.058)	(0.06)	(0.086)	(0.078)	(0.083)	(0.083)	(0.071)	(0.078)
exp3	0.214	0.213	0.213	0.222	0.234	0.223	0.203	0.188	0.199
	(0.061)***	(0.058)***	(0.06)***	(0.086)***	(0.078)***	(0.083)***	(0.083)**	(0.071)***	(0.078)***
exp4	-0.038	-0.042	-0.040	0.079	0.088	0.078	0.089	0.071	0.084
	(0.061)	(0.058)	(0.06)	(0.086)	(0.078)	(0.083)	(0.083)	(0.071)	(0.078)
exp5	-0.019	-0.012	-0.019	-0.018	0.003	-0.011	0.021	0.016	0.018
	(0.061)	(0.059)	(0.06)	(0.087)	(0.078)	(0.083)	(0.083)	(0.071)	(0.078)
Ssrule			0.202			0.086			0.099
			(0.042)***			(0.061)			(0.061)
Crule			0.106			-0.716			0.878
			(0.077)			(0.106)***			(0.105)***
Brule			0.156			-0.366			0.653
			(0.057)***			(0.073)***			(0.074)***
Sex			0.121						0.202
			(0.046)***						(0.064)***
Age			-0.015						-0.015
			(0.005)***						(0.007)**
Gpa			0.098						0.165
			(0.029)***						(0.039)***
Major						-0.105			0.351
						(0.061)*			(0.061)***
Finaid									-0.132
									(0.059)**
Work						-0.007			0.005
						(0.002)***			(0.002)**
Cred						0.001			
						(0.001)**			

Marry									-0.301 (0.106)***
Asian						0.191 (0.056)***			
Fixed Effect?	No	Yes	No	No	Yes	No	No	Yes	No
F		2.58			5.99			8.37	
Prob > F		0.000			0.000			0.000	
Rho		0.1169			0.2342			0.2970	
R2	0.7560	0.7548	0.7657	0.6248	0.6184	0.6555	0.5531	0.5514	0.6118
Subjects	52	52	52	52	52	52	52	52	52
Obs	1038	1038	1038	1038	1038	1038	1038	1038	1038

For each of the three dependent variables, regression (2) seeks fixed effect estimates, whereas regressions (1) and (3) do not. Any explanatory variable that is constant for a given subject cannot be included in a fixed effect regression, including the GROUP variable that distinguishes the penalty incentive from the bonus. Regression (1) includes only the variable GROUP among those that do not vary by subject, whereas regression (3) includes GROUP and other significant variables that do not vary by subject. These regressions allow us to test for fixed individual differences, obtain an indication of what individual characteristics might cause any observed fixed differences, and see how a change in the incentive frame affects the composition of decision performance. Before commenting on these results, we discuss how we control for problem complexity, luck, and experience.

The dummies task2, task3, and task5 indicate how performance at the complexity levels 2, 3, and 5 compare to performance on problems at the complexity level 4, since the task4 complexity dummy is left out of the regression. As would be expected, we find total decision performance gets significantly and progressively worse as the decision problem gets increasingly complex. The decision quality and decision efficiency regressions indicate that this decline in overall decision performance occurs both because poorer quality decisions are made and because more decision resources are used.

Because there is nothing to guide subjects in their initial trial choice, part of decision performance is the result of luck. Those who happen to select an initial trial close to the optimum will tend to experience a better decision performance regardless of their decision making ability. Hence, any fixed differences in decision behavior should be judged conditional upon the quality of the initial trial choice. To allow for a non-linear impact, we examine the effect of the initial trial non-parametrically. Let SDIFF denote the difference between S_{opt} and the number of search points associated with the initial trial choice. The variables luck10 through luck100 shown in Table 4 are dummies constructed from the distribution of SDIFF for the particular problem type. In particular, when luck10=1, the initial trial choice is in the top 10 percent of initial trial choices for the given problem type. In contrast, luck100=1 indicates the initial trial is among the lowest 10% in quality. The medium quality category luck50 was excluded from the regression to obtain identification, so the estimated coefficients on the luck dummies give the marginal impact relative to the luck50 category. The results presented in Table 4 demonstrate the importance of recognizing luck. On average, and as would be expected, a subject whose initial trial was closer to the optimum tended to perform significantly better. Moreover, the return to luck is increasing with luck. So, for example, moving from the second most lucky group (luck20=1) to the most lucky group (luck10==1) yields a greater improvement in decision performance than a move from the most unlucky group (luck100=1) to the next most unlucky group (luck90=1).

The dummy variable exp# is equal to 1 when the subject is solving a problem of a particular complexity level for the #th time. Overall, it appears that controlling for the effect of experience was not particular important. That is, the experience dummies do not significantly enhance the explanatory power of the model.

Controlling for problem complexity, luck, and experience, the fixed effect regressions (2) in Table 4 indicate there are significant fixed differences in decision behavior. These differences explain 11.7 percent of the variation in observed total performance, a sizeable portion. Decomposing total performance, the significant fixed individual differences in the use of decision resources (i.e., EFF) explain 29.7 percent of the variation in their use, while fixed differences in the ability to find high quality choices (i.e., SMAX) explain 23.4 percent of the variation in decision quality.

Fixed effects for total performance, decision quality, and decision efficiency are significantly correlated. The correlation between total performance and decision quality is 0.37 (p-value=0.0075), while the correlation between total performance and decision efficiency is 0.4382 (p-value=0.0012). At the same time, the correlation between decision quality and decision efficiency is -0.6007 (p-value=0.0000). This very strong negative correlation indicates subjects who consistently searched less also tended to be those who consistently made decisions of poorer quality, and vice versa. This result not only holds for all problems as shown here, but also for each problem type separately. Thus, we find people can be typed based upon how they obtain improved choices. Some improve by being more patient, effectively using more decision resources to make better choices. Others improve by being more decisive, sacrificing decision quality in order to conserve decision resources.

Regression (3) in Table 4 provides an indication of some observable individual characteristics that explain a portion of the fixed differences found in regression (2). Subjects with a higher GPA exhibited higher total decision performance, as did males, and younger subjects. The decision efficiency regression (3) indicates this superior total performance was enabled by the conservation of decision resources. That is, higher GPA students, males, and younger students were more decisive. Non-business majors made higher quality choices than business majors, as did those who worked fewer hours, those who took more credits, and those who were Asian. However, these significant differences in decision quality did not translate into higher overall decision performance because they were accompanied by an increased use of decision resources. Those who reported using some type of systematic search method performed better, and the regressions indicate having a method augments total performance both by conserving decision resources and by being more effective a finding higher quality choices.

The regressions in Table 4 indicate subjects under the penalty frame were significantly more conservative in their use of decision resources than subjects in the bonus frame, which is consistent with the results from the hazard model regressions.   That is, a penalty frame encourages decisiveness. The regressions in Table 4 indicate that this increased decisiveness lead to decisions of significantly lower quality on average so that overall performance was not better in the penalty frame compared to the bonus frame.

By including estimated fixed differences from a decision performance as an explanatory variable in a hazard model regression, we can examine how fixed differences in individual decision ability impact the probability of stopping the search. The fixed effect for a subject obtained from the total performance regression (2) in Table 4 measures how the subject performed overall relative to others. Adding this fixed effect variable ABIL to the All Tasks hazard model regression of Table 2 yields a hazard ratio of 3.56 (p-value 0.000) for the fixed effect variable. Thus, individuals who performed better on average tended to be more decisive. Thus, for these decision tasks, decisiveness is a virtue overall because it saves search costs.

Because expending additional search costs might well be productive, it is hard to believe decisiveness is always a virtue. To examine this issue, we added the variable ABIL to the 2 task, 3 task, 4 task, and 5 task hazard model regressions reported in Table 2, while also excluding the observations associated with the initial trial being extremely lucky (where luck10=1). For the 2 task and 3 task regressions, the hazard ratios for the variable ABIL were 7.7 (p=.000) and 11.3 (p=.000), respectively, so for these more simple problems decisiveness was a virtue. For the 4 task regression, the hazard ratio was .82 (p=.623), implying decisiveness is not a virtue. For the 5 task regression, the hazard ratio was .39 (p=.045), indicating those who performed consistently better were able to adjust, and be more patient and search longer when the problem was quite complex and the initial trial was not extremely lucky.

5. Conclusions

Bridger and Long (1984) claim that the process of seeking an optimum emulates key aspects of real world jobs.   We find fixed individual differences in the degree of patience/decisiveness exhibited by human subjects as they seek optima in our experiment, and we find that a change in the frame of the incentive from bonus to penalty alters the degree of patience/decisiveness exhibited by the average subject.   Males, business majors, those with GPAs, and who work more hours per week were more decisive, while Asians, those married, those with more college credits, and those receiving financial aid were more patient. We find people can be placed into two categories based upon how they improve their decision performance. Those more patient sacrifice more decision resources to make higher quality choices, while those more decisive sacrifice decision quality in order to conserve decision resources.

De Martino et al (2006) find that a framing bias is associated with activity in the amygdala, a region of the brain known for detecting and processing “emotionally relevant” information, and speculate that decision making based upon “emotional cues” has evolved because it is effective in particular environments.   In our experimental environment, a penalty frame encourages decisiveness in search, while a bonus frame encourages patience, suggesting these two frames spawn different emotions. This is consistent with work in psychology that indicates positive reinforcement motivates more effectively than negative reinforcement, while it is not consistent with the loss aversion element of prospect theory.

Our results suggest it is a mistake to assume decision ability can be measured by cognitive skills alone. Specifically, employers may benefit by matching individual temperaments and incentive frames with the task at hand. Our results suggest simple decisions should be made under an incentive framed as a penalty by workers chosen for their more decisive temperament. Alternatively, more complex decisions should be made under a bonus frame by workers chosen for their more patient temperament. Having demonstrated incentive frame and individual temperament impact choice in the laboratory, there is reason to think a field experiments may be useful for identifying the appropriate incentive frame and the most productive worker temperament for real world jobs.

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Appendix: Effort Allocation Game Instructions

Thank you for volunteering to play the Effort Allocation Game.

As a participant in this experiment, you will face 20 “effort allocation problems.” For each problem, there will be “tasks” you will have to “perform.” To perform a task, you must allocate “effort” toward it. You will be given an endowment of 200 units of effort. The decision you must make is how to allocate your 200 units of effort among the tasks. Allocating more effort toward one task allows you to perform that task more effectively. However, allocating more effort to one task means you must allocate less effort to some other task.

Your goal in allocating your effort is to make your “total earnings” as high as possible. Your earnings will be paid to you in the form of cash. Because you get the keep the cash that you earn, you have an incentive to do as well as you can on each problem. For a given problem, your total earnings is the sum of (1) your “wage,” (2) your “decision bonus” and (3) your “efficiency bonus.” These three types of earnings will now be described in more detail.

Your wage is the amount of cash you receive for the problem regardless of how you perform. Your wage will be 1 cent for each problem.

Your efficiency bonus is the amount of cash you are paid for conserving decision-making resources. If you accept your first trial as your choice and do so within 15 seconds, then you will receive the maximum efficiency bonus, which is 41.9 cents. A fraction of your efficiency bonus will be taken from you for each alternative allocation you try. (The computer will show you the cost of trying another alternative in terms of the efficiency bonus you will lose). The more alternatives you try prior to accepting a choice, the lower your efficiency bonus. You may try at most 25 alternatives. If you use all 25 alternatives, your efficiency bonus will equal zero, the computer will automatically accept your best trial alternative as your choice for the problem, and your total earnings will equal your wage plus your decision bonus. One further point, you have 15 seconds to try an alternative. If you wait longer than 15 seconds, you will lose a fraction of your efficiency bonus just as you would had you entered a trial allocation.

Your decision bonus is the amount of cash you earn based the quality of your choice. Better effort allocation choices generate larger decision bonuses. (Note: Your decision bonus can be negative.) Using trial and error, you can attempt to increase your decision bonus by searching for better ways to allocate your effort. For each allocation you try, the computer will display your “search points,” which is the decision bonus associated with the trial. To facilitate your memory, the computer will keep track of your prior attempts as you try different allocations, showing you your last two trials and your best trial.

After each try, you must decide whether to continue to search or stop your search. When you chose to stop, the computer records your best trial as your choice, and the decision bonus you

actually earn will be the search points associated with this best trial. To become familiar with the game, you will first be taken through a standard “administrative game,” where you will have the opportunity to experience first hand what you have read here. After completing the administrative game, you may ask questions so as to make sure you understand how the game is played.
Then you will play four “practice games,” where the first practice game involves a two task problem, the second practice game involves a three task problem, the third practice game involves a four task problem, and the fourth practice game involves a five task problem. Finally, you will play 20 “real games,” where the number of tasks involved will vary.

Remember, your goal is to maximize your total earnings over the 20 “real games.” Because each game is independent from the others, you will maximize your total earnings by doing as well as you can on each individual game. In each game, you can earn up to about 1 dollar (1 cent wage + 50 cent maximum decision bonus + 49 cent maximum efficiency bonus), meaning you can earn up to about $20 in total.

Good luck!