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DEFAULTS AND ATTENTION:
THE DROP OUT EFFECT

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Daniel J. Martin

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ABSTRACT

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Andrew Caplin
Department of Economics
New York University
19 W. 4th Street, 6th Floor
New York, NY 10012
and NBER
andrew.caplin@nyu.edu

Daniel J. Martin
Department of Economics
New York University
19 W. 4th Street, 6th Floor
New York, NY 10012
daniel.martin@nyu.edu

Defaults and Attention: The Drop Out Effect*

Andrew Caplin[†] and Daniel Martin[‡]

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Abstract

When choice options are complex, policy makers may seek to reduce decision making errors by making a high quality option the default. We show that this positive effect is at risk because such a policy creates incentives for decision makers to "drop out" by paying no attention to the decision and accepting the default sight unseen. Using decision time as a proxy for attention, we confirm the importance of this effect in an experimental setting. A key challenge for policy makers is to measure, and if possible mitigate, such drop out behavior in the field.

Key Words: Default Effects, Nudges, Bounded Rationality, Limited Attention, Rational Inattention, Mistakes

1 Introduction

When choice options are complex, consumers may be confused and thus make mistakes. Figure 1 shows that even a simplified presentation of the available Medicare plans in the U.S. requires decision makers to process a significant amount of information. For those seeking to understand

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[†]Center for Experimental Social Science and Department of Economics, New York University and National Bureau of Economic Research.

[‡]Center for Experimental Social Science and Department of Economics, New York University.

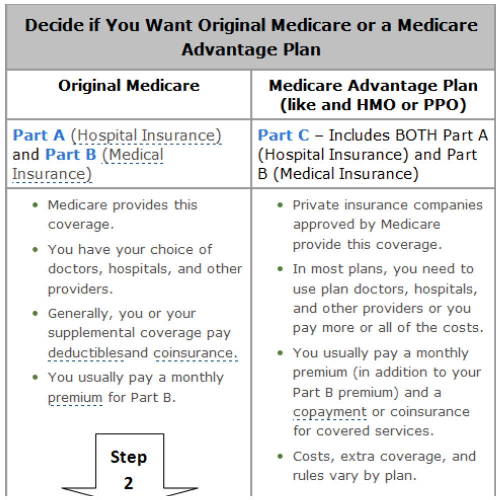

Figure 1: Screenshot from www.medicare.gov

the options and make a suitable choice, "spending an hour or two is not going to get the job done" (Thaler and Sunstein [2008], p.168).

In such complex decision environments, it is common for policy makers to make one option the "default", and to implement this option unless the decision maker actively opts out. In the past, it has been common for policy makers to use little or no discretion in selecting which alternative will be the default. This leaves decision quality somewhat to chance, since many decision makers appear reluctant to opt out of defaults (Madrian and Shea [2001]).[1]

Rather than set defaults in an essentially random manner, Thaler and Sunstein [2008] propose instead that policy makers deliberately select a default option that is as good as possible for those who blindly accept it. The policy goal in so selecting the default is to "help people who make errors while having little effect on those who are fully rational" (O'Donoghue and Rabin [2002], p.186). Just such a policy was implemented for Medicare choice in Maine, where in an effort to identify an appropriate default, "the ten plans meeting state coverage benchmarks were evaluated according to three months of historical data on prescription use" (Thaler and Sunstein [2008], p. 172). Analogous policies are now being considered, developed, and applied in many arenas, from choice of savings plan, through choice of consumer financial products, to choice of medical insurance options. Also under consideration is the "active choice" policy of Carroll, Choi, Laibson, Madrian, and Metrick [2009], which places the onus directly on the decision maker to make a choice, without

[1] See also Carroll, Choi, Laibson, Madrian, and Metrick [2009] and Beshears, Choi, Madrian, and Laibson [2011].

singling out a particular option as the default. Models of these various policies are advancing as well. Carroll, Choi, Laibson, Madrian, and Metrick [2009] model performance of these policies when decision makers have self-control problems and can delay decisions, while Carlin, Gervais, and Manso [2011] analyze how default policies impact social learning.[2]

In this paper, we model and measure experimentally the impact of deliberately set defaults on decision quality. In our model, when a policy maker deliberately makes an option the default, this designation provides information concerning the value of that option.[3] While we allow private attentional effort to provide further information on which choice is best, we find that there is a strong incentive to accept an informative default sight unseen. This "drop out" behavior, which operates on the *extensive* margin of attentional choice, contrasts with behavior in standard economic models of production and consumption, in which adjustment typically takes place on the *intensive* margin.[4] Strikingly, we find experimentally that informative defaults lead to a significant increase in such drop out behavior.

While the main channel in our theory of default effects is informational, there are other factors that contribute to drop out behavior. In particular, we find that somewhat fewer subjects drop out with the active choice policy than when they have a completely uninformative default, despite the informational equivalence of these policies. This means that the requirement of active choice per se may reduce drop out behavior and have a positive effect on decision quality. Our model is silent on the mechanism underlying this additional effect.

While drop out behavior may be mitigated by the active choice policy, it is nevertheless prevalent in all of our experimental treatments. In keeping with the aphorism that "you can lead a horse to water, but you can't make it drink," it appears you can lead a subject to choose, but you can't make him think. The prevalence of drop out behavior implies that choice data alone cannot identify the impact of defaults on choice quality when preferences are unknown. If few individuals opt out,

[2] Our model is complementary with both of these approaches. The random draw of "time cost" in Carroll, Choi, Laibson, Madrian, and Metrick [2009] is analogous to the marginal cost of attention in our model (see section 2), and the social benefit to attentional effort in Carlin, Gervais, and Manso [2011] could be added to the attentional production function in our leading example (again see section 2).

[3] The information content of defaults has been studied also by Madrian and Shea [2001], Brown and Krishna [2004], McKenzie, Liersch, and Finkelstein [2006], and Carlin, Gervais, and Manso [2011].

[4] Given their focus on social learning, Carlin, Gervais, and Manso [2011] exogenously fix the population division between attentive and inattentive DMs. There are a number of other important differences between our formulations, in particular what is learned through attentional effort (see section 3).

it may mean that many found the default option personally suitable, but it may also mean that many failed to attend to the choice.

This uncertainty surrounding improvements in choice quality raises a policy challenge. On the one hand, if decision makers are rational inattentive, as they are in our model, then even with the drop out effect, informative defaults are always welfare maximizing. On the other hand, default policies are often justified solely on the basis that they improve choice quality. Thaler and Sunstein [2008] argue that "setting default options, and other similar seemingly trivial menu-changing strategies, can have huge effects on outcomes, from increasing savings to improving health care to providing organs for lifesaving transplant operations" (p. 19).

Our work suggests a possible answer to this challenge: when choice data are enriched with a suitable measure of attentional effort, it is possible to separate out any drop out effects. In our experiment, we find that decision time, a particularly simple measure, serves as an excellent proxy for attention and is capable of identifying attentional drop outs.[5] While decision time can be cleanly recorded in the controlled environment of the experimental laboratory, it may be difficult to pin down in the field. Researchers interested in understanding the impact of default policies in the field will likewise need to develop measures of attentional effort appropriate for the settings they study.

In section 2 we present our model of attentional choice and begin our analysis of drop out behavior in the context of a simple example. In the following section, we model the policy setting. Section 4 generalizes the model and formalizes the "Drop Out Hypothesis", which asserts that the replacement of a random default with an informative default increases the number of inattentive decisions. Section 5 presents the complementary experimental design and identifies the effect of an informative default on decision quality. Section 6 confirms the Drop Out Hypothesis and shows that this increase in inattentiveness significantly impacts decision quality. Section 7 presents experimental findings on the active choice policy. Section 8 concludes.

[5] We thank Muriel Niederle for pressing us to explore the validity of decision time as an attentional proxy. The time taken to reach a decision is regularly studied in psychology, in part because drift diffusion models explicitly include it (see Ratcliff and McKoon [2008]). However, decision time has been little studied in economics. Exceptions include Wilcox [1993], Rubinstein [2007], Geng [2011], and Reutskaja, Nagel, Camerer, and Rangel [2011].

2 Attentional Choice and Drop Out Behavior

In this section, we use an example to introduce our information theoretic model of the costs and returns to attentional effort. We show in this example that drop-out behavior, in which attentional effort is set to zero, is optimal when costs are high enough. We show in section 4 that this insight concerning the role of the extensive margin of attentional choice is far more general.

Looking beyond the example, it is clear that the precise trigger for inattention is situation-specific. It depends both on the difficulty of learning in the problem at hand and on the extent of the information that is available absent attentional effort. We illustrate in this section how these forces shape the level of attentional effort that is chosen.

2.1 Costs of Attention

Choice does not require understanding. On the one hand, decision makers (DMs) can accept the default option, or select a different option, understanding little to nothing about the available options. On the other hand, they can choose to devote attention to gain greater understanding of these options. For example, in the case of Medicare, they can read in detail the description of each plan, match it to personal health circumstances, join on-line discussion forums, etc. To capture this, we allow DMs to choose whether or not to attend to a given choice, and if so, how much attentional effort to make. The chosen level of attention is captured by intensity measure $\alpha \geq 0$, with higher levels of α corresponding to more intense effort to clarify the precise payoffs of the available options.

We assume for simplicity that the attentional decision is made just once before an option is chosen and cannot be revised. The costs of attentional effort (in expected utility units) are assumed linear in the level of attention,

$$K(\alpha) = k\alpha.$$

The parameter $k > 0$ is the marginal utility cost of attentional effort. This parameter is allowed to vary both across individuals and across time, yet is assumed known to each DM when the level of attentional effort is chosen.

2.2 Payoff Uncertainty and Signals: An Example

We model DMs who face uncertainty concerning the payoffs to a set of available choices and can reduce this uncertainty by expending attentional effort to obtain informative signals about the state of the world. The resulting reduction in payoff uncertainty improves the quality of final decisions and thereby raises expected utility.

Our main example involves two actions, choose the option on the left (a_L) or choose the option on the right (a_R), and two prizes, a good one (x_1) and a bad one (x_2), with normalized expected "prize" utility of $U(x_1) = 1$ and $U(x_2) = 0$. The DM knows that one and only one of the two actions will yield the preferred prize x_1. Which action yields x_1 is determined by state $\omega \in \{\omega_L, \omega_R\}$. In state ω_L the preferred prize is on the left, while in state ω_R it is on the right. We assume that the good prize is ex ante more likely to be on the right, with,

$$\Pr(\omega_R) = \frac{2}{3}.$$

A fully-informed DM who knows the true state of the world would always pick a utility maximizing option. Errors are made only because DMs do not perfectly perceive the state of the world, so they do not fully understand the consequences of the available actions. Before making an action choice, the DM can get up to two signals about the state of the world. Each signal either suggests that the good prize is on the left (σ_L) or on the right (σ_R). When the good prize is actually on the left, the signal is correct with probability $\frac{3}{4}$, and when the good prize is actually on the right, the signal is also correct with probability $\frac{3}{4}$, so that,

$$\Pr(\sigma_L|\omega_L) = \Pr(\sigma_R|\omega_R) = \frac{3}{4}.$$

2.3 The Benefits of Attention

Choice of attentional effort depends on a production function that turns this effort into a probability distribution over the number of signals received. We assume that there are logistic returns to attention: signals are received with probability $\frac{1}{1+e^{-(6\alpha-6)}}$, and if signals are received, there is an equal probability of getting 1 or 2 signals. This reflects initial increasing returns to attention and then decreasing returns.

To compute optimal attention, we first determine the expected prize utility for different signal realizations by calculating posterior beliefs (after receiving any signals and before making an action choice) about the location of the good prize for all available actions. In the example, when no signals have been received, the right action a_R is more likely to yield the good prize and is therefore the best choice. The corresponding expected prize utility is,

$$V_0 = \frac{2}{3}.$$

The best choice with one signal depends on its direction. If it indicates that the good prize is on the right (a signal of σ_R), this confirms a_R as the better choice. If it indicates that the good prize is on the left (σ_L), then a_L becomes the better choice since the signal is more informative than the prior. Overall, the good prize is chosen if and only if the state is ω_L and the signal is σ_L or the state is ω_R and the signal is σ_R, so the corresponding expected prize utility is,

$$V_1 = \frac{2}{3} \cdot \frac{3}{4} + \frac{1}{3} \cdot \frac{3}{4} = \frac{3}{4}.$$

The outcome with two signals is clear. If they are both σ_R or one is σ_R and the other is σ_L, then a_R is chosen. If they are both σ_L, then a_L is chosen. Overall, the expected prize utility with two signals is,

$$V_2 = \frac{2}{3} \cdot (1 - \frac{1}{16}) + \frac{1}{3} \cdot \frac{9}{16} = \frac{39}{48}.$$

Combining the signal production function with the results above yields the AVF,

$$V(\alpha) = \frac{1}{1 + e^{-(6\alpha - 6)}} \cdot \frac{25}{32}.$$

This AVF is presented in Figure 2. Note that the AVF resembles a logistic function: it starts out convex and then becomes concave.

2.4 Optimal Attention and Drop Out Behavior

To determine the optimal level of attention, the DM weighs the costs of attention, given by $K(\alpha)$, against the benefits of attention, given by $V(\alpha)$. The simple calculus of optimal attention is illustrated in Figure 2. The only possible optima are to put in zero attentional effort or to put in an effort level that creates a tangency (at the effort level α' in the figure) with marginal cost on the concave boundary of the convex hull of the AVF (shown with a dashed line in the figure). To work

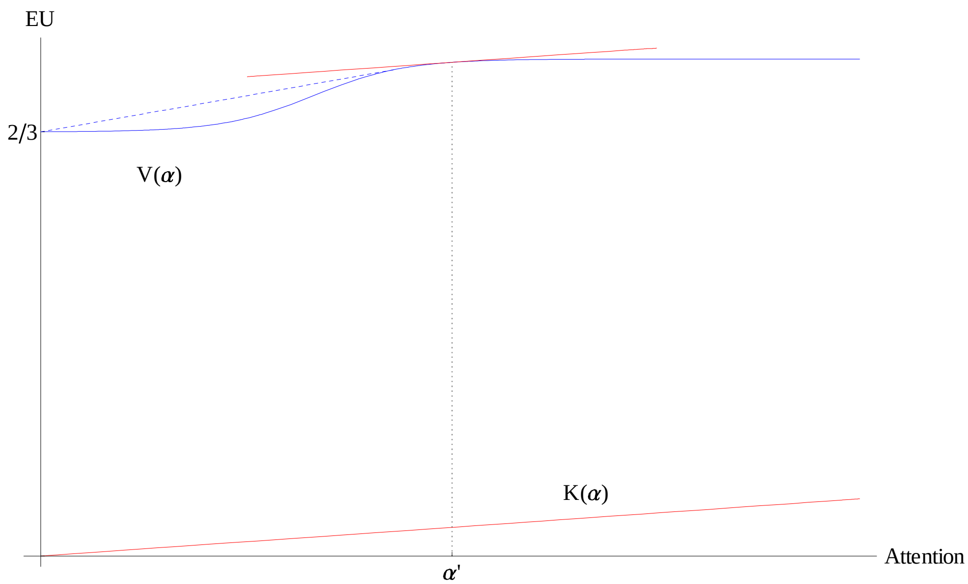

Figure 2: Example of the costs and benefits of attention

out which of these is superior, one compares the horizontal difference $V(0)-K(0)$ to $V(\alpha')-K(\alpha')$. When $K(\alpha) = .03\alpha$, as in Figure 2, the optimal level of attention equals approximately 1.5. The expected utility given by the AVF at this optimal level of attention indicates average choice quality for a specific marginal cost of attention.

As indicated above, we allow for heterogeneity in the costs of attentional effort. We introduce the function $\hat{V}(k)$ to capture the relationship between the marginal cost of attention and choice quality,

$$\hat{V}(k) = V(\alpha^*),$$

where $\alpha^* \in \arg\max_{a\geq 0}\{V(\alpha) - k\alpha\}$.

In Figure 3, we plot $\hat{V}(k)$ for the AVF computed in the example above. Note that as the cost of effort rises above zero, there is a gradual reduction in decision quality as the DM chooses lower levels of attentional effort. At a critical cost level, marked as $\bar{k}$ in the figure, it is optimal to drop out altogether and to choose zero attentional effort. At this point, we see rational inattention.

The key finding above is that optimal effort is zero for costs of attention above a critical threshold $\bar{k}$. We show in section 4 not only that such a threshold exists in all reasonable cases, but also that the cutoff threshold is generally reduced when there is an informative default. This result is formalized in the Drop Out Hypothesis.

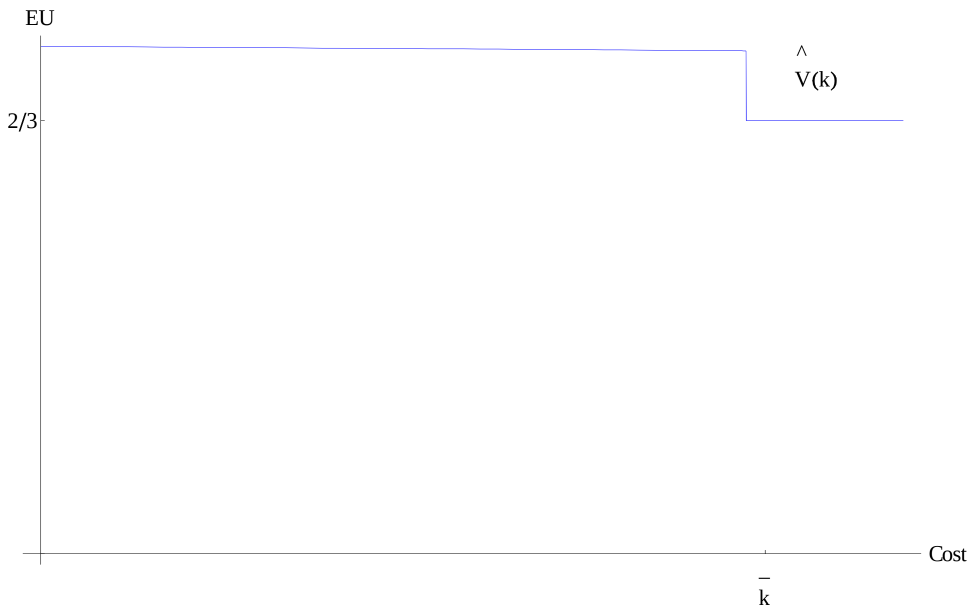

Figure 3: Choice quality given effort cost

3 Policy and Decision Quality

In this section, we add a policy context to our model in order to explore the impact of defaults on attentional choice. We then extend the example of the previous section to capture policy effects. To do so, we first make explicit the information theoretic underpinnings of our general model of attentional choice.

3.1 Modeling Uncertainty

Note in the example that we separated out action choices, a_L and a_R, from the utility-relevant consequences of these actions, which is receipt of either prize x_1 or x_2. In our policy setting, we follow Caplin and Martin [2012] in allowing for an arbitrary set $A = \{a_m | 1 \leq m \leq M\}$ of available actions and an entirely distinct finite set of prizes $X = \{x_n | 1 \leq n \leq N\}$, over which DMs have preferences. Each action corresponds to a position in a list, a location on a computer screen, a particular slot machine, etc. In the example above, the set of available actions was to choose the option on the left or the right. Importantly, these action-defining properties should be easily observable as they assumed to be objectively identified and understood by all DMs immediately upon being faced with the choice problem.

The state of the world is the true underlying assignment of prizes to actions, $f : A \to X$. In the example above, the assignment was whether the prize x_1 was on the left or the right.[6] We assume that this assignment is set by the policy maker, but not fully known by DMs, who apply attentional effort to improve their understanding of the mapping. DMs start out with a prior on the set of states, $\mu \in \Delta(\mathcal{F})$, with $\mathcal{F} \equiv \{f : A \to X\}$.[7]

However natural it may be in the context of complex choices, this separation of actions from prizes is not standard. Carlin, Gervais, and Manso [2011] use the more standard approach in modeling states of the world where the objective consequences of all actions are clear, yet how much prize utility each action provides the DM is unknown. While one could in principle derive precisely the same results in this alternative framework, our model allows uncertainty to relate to objectively measurable data rather than subjective types. This both guides experimental implementation and suggests obvious comparative static properties. In our framework, an increase in the complexity with which given objects are displayed directly impacts returns to attentional effort. Similarly, making it hard to view all options simultaneously lowers attentional returns. A standard type-based model does not naturally accommodate these effects, since the maintained assumption is that all objective consequences are perfectly understood regardless of how clearly they are presented.

3.2 Policy Options

The policy maker starts with a fixed set X^C of options, which is the choice set that will be presented to all DMs.[8] The identity of X^C is the private information of the policy maker, but it is common knowledge that X^C is a subset of the grand prize set X and that the size of X^C is M. There is a corresponding fixed action set of the same cardinality $A = \{a_1, .., a_M\}$, where a fixed action $a^* \in A$ is the default action, which is also common knowledge. In this setting, the policy maker's only choice concerns which prize to assign to the default action. One possible policy is to set a random default.

[6] This separation of actions from prizes also characterizes the classical "bandit" problem, in which an act is the choice of a bandit arm and choice is guided by the DM's beliefs concerning the rewards and information provided by taking each action. The bandit model has been fruitfully developed as a model of boundedly rational choice by Bolton and Faure-Grimaud [2009].

[7] Note that what we define here as states of the world are referred to as "frames" in Caplin and Martin [2012].

[8] This model can be extended to make choice of this set endogenous.

- **Random Default**: In this policy, all prizes in X^C are assigned to the default action with equal probability. Thus, the policy maker knows that a DM who blindly chooses the default action is equally likely to get any prize in X^C. To complete the description of this policy, we assume that all prizes in X^C are equally likely to be assigned to any other action.

The informative default policy is the policy maker's alternative to a random default policy. Given our focus on attentional effort with informative defaults, we follow Carroll, Choi, Laibson, Madrian, and Metrick [2009] and Carlin, Gervais, and Manso [2011] in assuming that there is no conflict between the preferences of the policy maker and of the decision makers.[9] Hence if all DMs have identical preferences, the policy maker will simply select a utility maximizing option as the informative default option. With population heterogeneity, the policy maker needs to aggregate heterogeneous preferences. We assume it is commonly understood that the policy maker will maximize overall choice quality if all were to accept the default.[10] To formalize this, we assume that there is some decision maker type space T and that the policy maker's goal is to maximize a population weighted average of some normalized type-specific EU functions, $U_\tau : X \to \mathbb{R}_+$. As in Carroll, Choi, Laibson, Madrian, and Metrick [2009] and Carlin, Gervais, and Manso [2011], the policy maker knows the population distribution $\lambda \in \Delta(T)$.[11]

- **Informative Default**: In this policy, the prize $x^* \in X^C$ assigned to the default action maximizes the average level of normalized utility across the population if all were to accept it,

$$x^* \in \arg\max_{x \in X^C} \sum_{\tau \in T} \lambda(\tau) U_\tau(x).$$

In this policy, all other prizes in X^C are equally likely to be assigned to any other action.

[9] By way of contrast, the classical sender-receiver model of Crawford and Sobel [1982] analyzes how the motive of the policy maker impacts the feasibility of transmitting informative messages. Altmann, Falk, and Grunewald [2012] study default selection and reaction to defaults in the sender-receiver framework and show that default effects depend on the extent of the alignment in preferences between sender and receiver.

[10] This is similar to the optimal choice rule for policy makers in Carlin, Gervais, and Manso [2011]. Other rules for selecting informative defaults could be considered, but this one seems plausible and simplifies the strategic considerations.

[11] In our model, it is not necessary to specify the correlation between types and attentional costs. In principle, both the random processes generating marginal costs of attention and the AVFs could be type specific.

We assume that the policy maker must publicly and irrevocably commit either to the random default policy or the informative default policy. This policy rule is applied at a broader level than the individual decision problem under current consideration, so that policy makers cannot set a different default for different types.

3.3 Information Asymmetries and Default Policy

The model involves a natural asymmetry of information. The policy maker knows the set of prizes $X^C \subset X$ available to DMs and determines the mapping f from actions to prizes. By contrast, while DMs know the grand set of prizes X, the set of available actions A, that $a^* \in A$ is the default action, and the nature of the default policy, they may be quite uncertain about the contents of X^C and the mapping f from actions to prizes. Prior beliefs about f, and thus how likely each action is to yield each prize, will depend on the policy itself, as detailed below.

In our model, DMs know their precise type and hence their utility functions. However, they know less than the policy maker about the population distribution of types. Their beliefs about the population distribution impact their interpretation of an informative default because that distribution determines the prize assigned to the default action.

To analyze the impact of DM beliefs about the population distribution of types on the information conveyed by the default, we extend the example of the last section. In this extension, we use the simplifying assumption that DMs all regard themselves as more likely to be in the largest group, precisely according to the proportions in the broader population. Hence, all believe ex ante that the informative default is the best option for them.[12] It is only when they attend to the decision problem that they may come to understand that, while it may be suitable for others, the default does not suit their particular tastes.

3.4 Random and Informative Defaults: An Example

In the two action, two prize, two state, two signal example of the last section, let a_R be the default action.

[12] It is not necessary in the model to have such stark beliefs. Decision makers could have richer information about the distribution of types than in the example. They may, for example, suspect that they are in the minority and therefore have an incentive to switch away from the default.

We assume that there are two different types with distinct preferences. We specify that the policy maker knows that 2/3 of the population is of type τ_1 and prefer x_1 to x_2, while 1/3 of the population is of type τ_2 and has the reverse preference. For simplicity, we assume that the policy maker applies a simple normalization in which they are effectively interested in maximizing the probability that the best prize is picked regardless of type,

$$U_1(x_1) = U_2(x_2) = 1;\ U_1(x_2) = U_2(x_1) = 0.$$

What this means is that, in the informative default condition, the optimal choice for the policy maker is to have the default action yield prize x_1, so that,

$$f(a_R) = x_1.$$

As mentioned above, DMs all believe that their preference is likely to be in the 2/3 majority: those who prefer x_1 to x_2 are correct, while those who prefer x_2 to x_1 mistakenly assume that they are in the majority. Hence all DMs believe that there is a 2/3 chance that they will prefer the default action if they have seen no signals. Hence all will pick a_R and receive x_1 with the result that expected prize utility with no signals when there is an informative default is,

$$V_0^I = \frac{2}{3}U_1(x_1) + \frac{1}{3}U_2(x_1) = \frac{2}{3}.$$

The optimal choice with one signal depends on the DM's prize utility type and the direction of the signal. If the signal is σ_R, suggesting that x_1 is on the right, it confirms a_R as the better choice for those of type τ_1, but suggests a change to a_L for those of type τ_2. If the signal is σ_L, it confirms a_R as the better choice for those of type τ_2, while inducing type τ_1 to switch to a_L. In both cases, the type-specific best object is chosen if and only if either the state is ω_L and the signal is σ_L, or the state is ω_R and the signal is σ_R,

$$V_1^I = \frac{3}{4}\left[U_1(x_1) + U_2(x_2)\right] + \frac{1}{4}\left[U_1(x_2) + U_2(x_1)\right] = \frac{3}{4}.$$

By analogous logic, the expected prize utility for an informative default and two signals is just as in the previous example,

$$V_2^I = \frac{39}{48}.$$

Figure 2 summarizes the expected AVF based on this informational default just as it did the individual AVF. These coincide because the prior in the previous example matches the prior induced by the informative default in this example.

With a random default, each action is equally likely to produce either good, so that absent attention, each individual correctly regards each choice as having a 0.5 chance of delivering their preferred good,

$$V_0^R = \frac{1}{2}\left[U_1(x_1) + U_2(x_2)\right] + \frac{1}{2}\left[U_1(x_2) + U_2(x_1)\right] = \frac{1}{2}.$$

The optimal choice with one signal depends on the direction it points. If it points to the right, this suggests that a_R is the better choice for τ_1, a_L for τ_2. If it points to the left, these type choices are reversed. In all cases, the probability of picking the best action depends only on how informative is the signal, so that,

$$V_1^R = \frac{3}{4}.$$

Choice behavior with two signals continues in this vein. If they are both σ_R (5/16 chance), then a_R is the choice for τ_1, a_L for τ_2. If they are both σ_L (5/16 chance), the choices are reversed. In both cases, there is a $\frac{9}{10}$ chance that the correct choice is made, since according to the signal process two σ_L/σ_R signals are nine times more likely in state ω_L/ω_R than in the opposite state. Finally, if the two signals point in different directions (6/16 chance) then any choice is equally likely to yield either prize. Hence,

$$V_2^R = \frac{5}{8} \cdot \frac{9}{10} + \frac{3}{8} \cdot \frac{1}{2} = \frac{3}{4}.$$

Given the signal production function that turns attention into a probability distribution over the number of signals received, we can derive the function $V^R(\alpha)$ as,

$$V^R(\alpha) = \frac{1}{1 + e^{-(6\alpha - 6)}} \cdot \frac{3}{4}.$$

The functions $V^R(\alpha)$ and $V^I(\alpha)$ are illustrated in Figure 4.

3.5 Which Policy Maximizes Expected Choice Quality?

In Figure 5 we show expected choice quality as it depends on the marginal cost of attention with the informative default and with the random default. Note that the critical level of attentional cost at which it is optimal to drop out is strictly lower when there is an informative default than when the default is random,

$$\bar{k}^R > \bar{k}^I.$$

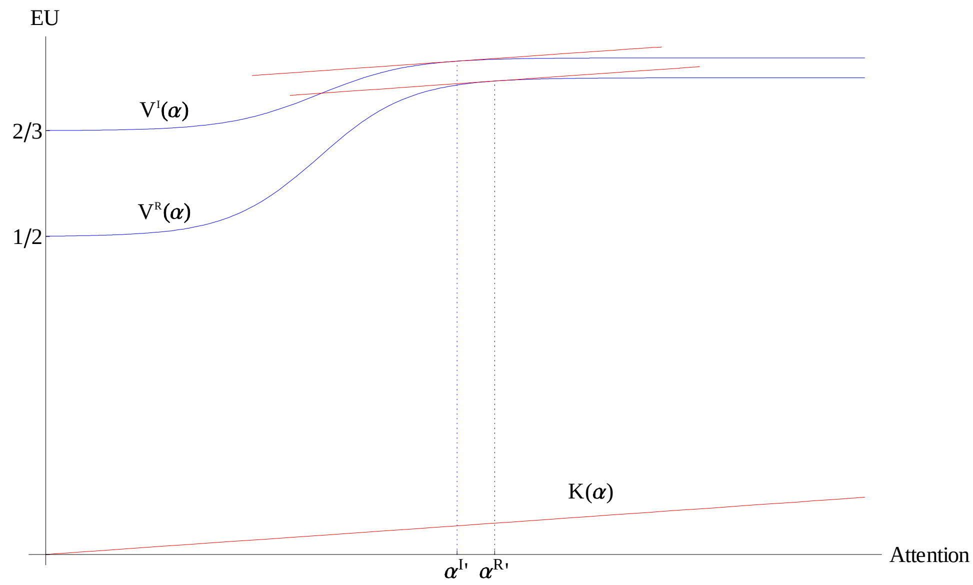

Figure 4: Example of optimal attention in policy setting

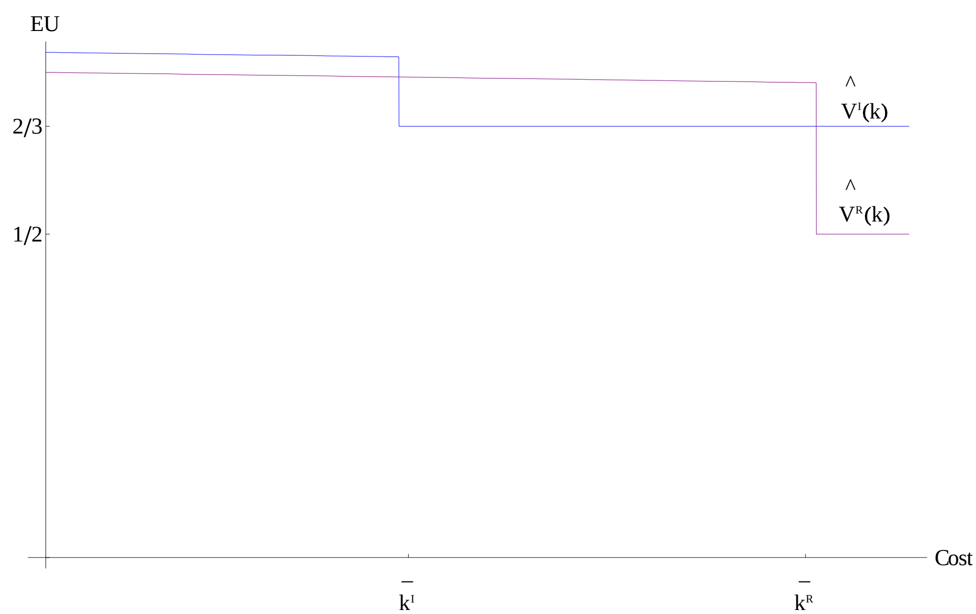

Figure 5: Choice quality given effort cost in policy setting

There are three distinct attentional cost regions in terms of decision quality. For high levels of cost, $k > \bar{k}^R$, there is no attentional effort with either form of default. In this range, the higher information content in the default implies that average decision quality is higher. For low levels of cost, $k < \bar{k}^I$, there is attentional effort with both the informative and the uninformative default, and once again higher decision quality. The most interesting region is where there is positive attention only with the uninformative default,

$$k \in \left(\bar{k}^I, \bar{k}^R\right).$$

In this case, Figure 5 shows that choice quality is higher with the random default, given the attentional effort it induces, than with the informative default, for which drop out behavior is optimal. On balance, which policy produces higher choice quality depends on the distribution of attentional costs.

3.6 The Policy Maker's Objective

The analysis above shows that there may be circumstances in which so many DMs drop out in the face of an informative default that decision quality actually falls as a result. In such circumstances, a policy maker concerned with improving decision quality would choose the random default over the informative default. On the other hand, if the policy maker seeks to maximize expected utility (considering both the benefits and costs of attention) regardless of choice quality, it is always best in our model to use the informative default because decision makers are rationally inattentive. Carroll, Choi, Laibson, Madrian, and Metrick [2009] and Carlin, Gervais, and Manso [2011] show that this conclusion is fragile to the inclusion of self-control problems and social learning effects, and the same is to be expected if these approaches were combined with ours in a hybrid model.

4 The Drop Out Hypothesis

In this section, we establish that the impact of the informative default in incentivizing additional drop out behavior generalizes far beyond the simple example above.

4.1 The Attentional Value Function

We now introduce a general attentional value function to summarize the relationship between attentional effort and expected prize utility. The assumptions on this function are minimal: that additional effort cannot reduce expected prize utility, and that there is a bounded return to attentional effort at zero effort. The fact that this function maps into $[0, 1]$ is due to the normalization of expected prize utility: the best prize has an expected prize utility of one and the worst prize has an expected prize utility of zero.

Condition 1 *The attentional value function (AVF)* $V : \mathbb{R}_+ \longrightarrow [0, 1]$ *satisfies:*

1. Weak Monotonicity: $\alpha_1 > \alpha_2 \Longrightarrow V(\alpha_1) \geq V(\alpha_2)$.

2. Non-Triviality: $\exists\ \alpha_1 > \alpha_2$ such that $V(\alpha_1) > V(\alpha_2)$.

3. Bounded Returns: $\exists K > 0$ such that, for $\alpha = 0$ and $\delta > 0$,

$$\frac{V(\alpha + \delta) - V(\alpha)}{\delta} < K.$$

As illustrated in Figure 4, the example of the last section produces AVFs that satisfy Condition 1.

In practice, the shape of the AVF will be highly context specific. For instance, in the case of Medicaid choice, one might expect an initial region in which little if any learning takes place. This is reflected in the low initial rate of learning in the example. In even simpler environments, the AVF may be entirely concave, with the most rapid learning taking place at the lowest levels of attentional effort.

4.2 A Drop Out Cost Lemma

Figures 3 and 5 illustrate the first key feature of our general model, which is that there is an attentional cost $\bar{k} > 0$ such that optimal attention is zero if and only if costs are at or above this level. We provide a geometric proof of this result below, noting also that optimal effort is increasing as costs fall further below this critical level.

Lemma 1 *For any AVF $V : \mathbb{R}_+ \longrightarrow [0,1]$ satisfying Condition 1, there exists $\bar{k}$ such that $\alpha = 0$ is an optimal choice if and only if $k \geq \bar{k}$.*

To establish this result, note first that when the AVF is concave, Condition 1 implies that the AVF is right differentiable at $\alpha = 0$ as the limit of an increasing sequence that is bounded above by K,

$$\lim_{\delta \searrow 0} \frac{V(\delta) - V(0)}{\delta} \in [0, K].$$

The concave case is more general than it appears. Given the linearity of the cost function, it is clear that the optimal choice of attentional effort cannot lie on any convex portion of the AVF. This implies that the minimum optimal attentional effort level is unchanged if one uses the concave boundary of the convex hull of the AVF instead of the AVF.

Figure 2 illustrates the geometric construction for the given AVF which is non-differentiable and neither convex nor concave. By taking the convex hull of the graph, it becomes geometrically clear that all optima for the given AVF are also optimal for the concave boundary of the convex hull of the graph. The tangent lines also reveal that the optimal attention levels are at least weakly decreasing in the marginal cost of attention.

The Lemma applies not only with linear costs of attentional effort, but more generally with any cost function that is strictly increasing in attentional effort and has bounded returns at zero attention. Given such a strictly increasing cost function, one can identify a strictly monotone transformation of the attention argument with a bounded derivative such that the composite cost function is linear in the transformed effort variable. The value is unchanged if one correspondingly transforms the AVF. Condition 1 is maintained under this transformation, and the result follows. In that sense, one can regard linearity of the attentional cost function as a normalization used to define the level of attention rather than as a substantive restriction.

4.3 Drop Out Comparative Statics

We establish under broad conditions that the informative default incentivizes additional drop out behavior.

Proposition 1 *For V^I and V^R that satisfy Condition 1, if (i) $V^I(0) > V^R(0)$ and (ii) $V^I(\alpha) -$*

$V^R(\alpha) \in [0,\ V^I(0) - V^R(0)]$ *all* $\alpha > 0$*, then the drop out cost is at least as high with the random default as with the informative default, so that* $\bar{k}^I \leq \bar{k}^R$*.*

The proof of Proposition 1 follows directly from the geometric construction used in Lemma 1 applied to the convex hulls of the graphs of the two functions V^I and V^R.

The first condition requires that with no attention whatever, the informative default raises expected prize utility. This is generically the case in a very wide class of models. The reason for this is that, by definition, the uninformative default leaves the DM indifferent between all choices ex ante. Unless this precise indifference is sure to be maintained in the face of the updating induced by the specification of a default, the expectation must be that there will be contingencies in which one action yields strictly higher than prior average prize utility when there is an informative default.

The second condition comes in two parts. The first part asserts that the improvement in expected prize utility with no information is never reversed: expected prize utility associated with the decision is always at least as high when there is a default than when there is no default. The second part asserts that the increase in expected prize utility never be higher than when there is no attention. This makes sense if the impact of the prior reduces with attentional effort. Both parts of this condition are satisfied in the example.

This proposition directly gives rise to our Drop Out Hypothesis.

Definition 1 *The Drop Out Hypothesis is that replacement of a random default with an informative default induces an increase in the number of inattentive decisions.*

5 Experimental Design and Decision Quality

5.1 Measuring Decision Quality

The main goal of our experiment is to test the Drop Out Hypothesis. One requirement is to have a simple measure of decision quality. To achieve this, we use a task in which the subject has to identify which of three options has the highest numeric value. In this context, a natural measure of decision quality is the proportion of experimental runs in which the "best" option (highest value)

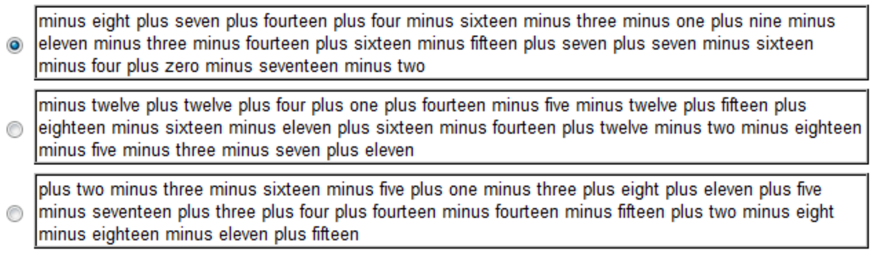

Figure 6: Screenshot of a typical round

was chosen.[13] The only intricacy is that the value of each option is hard to assess since it is expressed in words as the sum of twenty integers (as in Caplin, Dean, and Martin [2011]). Subjects were told that each of the 20 numbers was drawn independently and uniformly from integers between -18 and 18 (see online appendix for complete instructions). Figure 6 shows three such options.

5.2 Defaults and Beliefs

The first option is always the default option, meaning that it was preselected when each round began.[14] Subjects were allowed to change which option was selected at any time and as many times as they wished before clicking a button that was labeled "Finished."

We remove the policy making role from our experimental test because we are primarily interested in the behavior of DMs given different priors about the suitability of the default. Thus, we directly announce the probability that the default is best. We interpret knowledge of these probabilities as the end process of either direct knowledge of the rule used to select a default, as in the model, or experience with the default.

Subjects faced three treatments in each session, each of which represents a different probability that the default is best. In the "33%, 33%, 33%" treatment, subjects were informed that the default option had a 33% chance of being the highest valued option because a number was drawn randomly from three 1's, three 2's, and three 3's, and that the highest valued option was placed in the corresponding position in the list. They were also told that the remaining two options were randomly placed in the remaining positions and that this resulted in an equal chance of the option

[13] In just 4 of 1908 rounds, more than one option has highest value in that round, so there are two "best" options.

[14] While it is potentially interesting to consider cases when the default option is not first in the list, this seems less common in practice.

in each position having the highest value. In the "40%, 30%, 30%" treatment, subjects were given a similar mechanism, but which resulted in the default option having the highest value with a 40% chance and the other two options with a 30% chance.[15] Finally, in the "50%, 25%, 25%" treatment, a similar mechanism gave the default option a 50% chance of having the highest value, and the others a 25% chance.

Each treatment lasted 12 rounds, and the order of these 3 "blocks" of rounds was randomized. No feedback about performance was provided at any point during the experiment. Also, there was no time limit in each round, and subjects could leave the laboratory whenever they completed all 36 rounds. On average, subjects were in the laboratory for less than 1 hour – the minimum total time was 30 minutes, and the maximum total time was over 2 hours. Before a subject left the laboratory, three of the 36 rounds were randomly selected for payment.[16] In each round selected for payment, if the subject chose the best option, the payment was $8, and if the subject did not choose the best option, the payment was $4. Thus, the maximum total payment was $24, and the minimum total payment was $12. There was no show up fee.

Over 4 sessions, we observed a total of 53 students complete 1908 rounds (636 rounds per treatment). All sessions were run the Center for Experimental Social Science laboratory, and subjects were drawn from the undergraduate population at New York University.

5.3 Do Better Defaults Improve Choices?

Because there is an objectively best answer in each round, we can measure subject decision quality by the percentage of rounds in which the best option was chosen. Table 1 shows that while decision quality does not differ noticeably between treatments, decision quality drops for all treatments after the first 12 rounds.[17] This drop in decision quality is explained in our model by a shift in the distribution of attentional costs due to fatigue.

In fact, none of the pairwise comparisons of decision quality level between treatments, within

[15] Here a number was drawn randomly from four 1's, three 2's, and three 3's.

[16] Payment procedures were announced in advance to reduce disruption as subjects departed the laboratory. However, these departures may have introduced some peer effects.

[17] Unlike de Haan and Linde [2011], we do not find evidence that a more informative default in the first block of rounds hurts performance in the second block of rounds.

blocks or overall, are significantly different at the 10% level using a two-sided t-test.[18]

Table 1. Percent of rounds best option chosen

		Rounds			
Treatment	n	1-12	13-24	25-36	Overall
33%, 33%, 33%	636	62%	48%	54%	55%
40%, 30%, 30%	636	66%	51%	52%	55%
50%, 25%, 25%	636	62%	55%	55%	58%
Overall	1,908	63%	51%	54%	56%

The basic finding is that an informative default does little to improve choice quality on average. One possibility is that the default has no effect on choice behavior, which we will clearly reject. Another possibility comes from the Drop Out Hypothesis: that informative defaults increase drop out behavior.

6 Decision Time and the Drop Out Hypothesis

6.1 Revealed Inattention

As noted in the introduction, we measured not only the choices made but also the time taken to arrive at the decision.[19] We treat this decision time measure as a proxy for attentional effort. Across treatments the average decision time was 43 seconds, with a standard deviation of 58 seconds. The cumulative distribution function of decision times across treatments is given in Figure 7.

This measure allows us to observe changes on the intensive margin of attention (how much attentional effort is exerted) and the extensive margin of attention (whether any attentional effort is exerted). For changes in the intensive margin of attention, we compare raw decision times, contingent on a subject having appeared to exert any attentional effort. To determine whether a subject has exerted any such effort, we look both at the speed in which decisions are made and the average quality of the resulting decisions.

Rather than selecting an arbitrary time at which we feel that subjects have begun to pay

[18] Probit regressions run with clustering at the subject level produce the same results.

[19] In many settings, both in the lab and the field, it is possible to collect information on the time it takes to reach a decision.

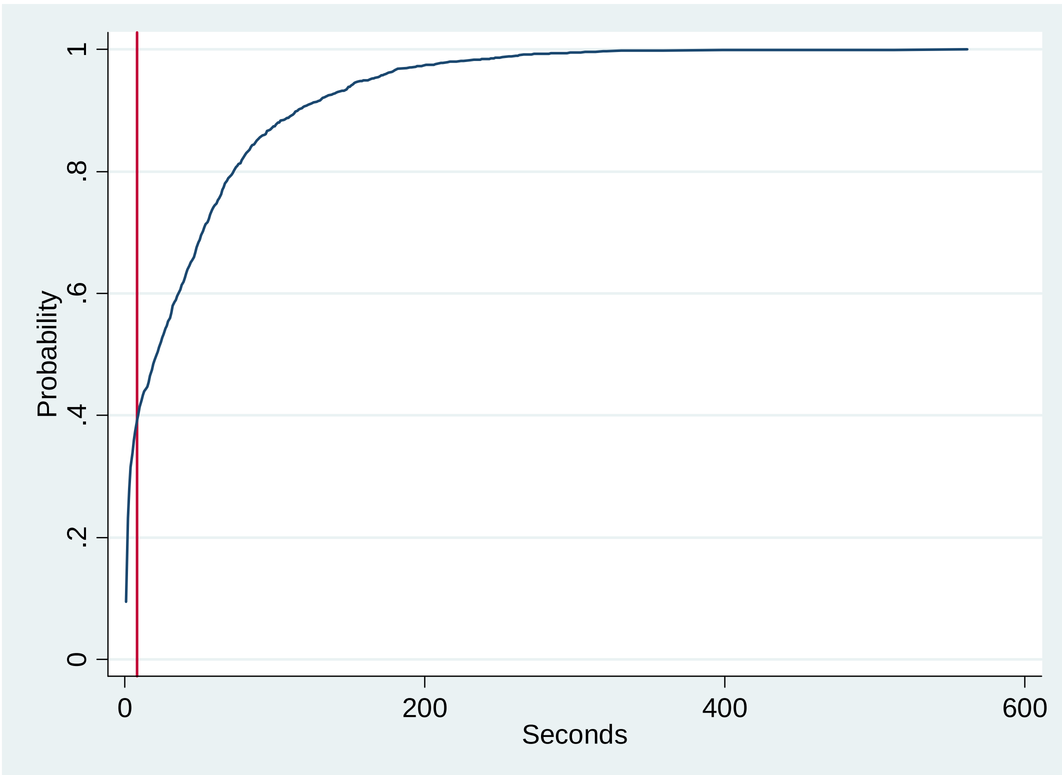

Figure 7: Cumulative density function of decision times

attention, we use the data to suggest an appropriate time. To do this, we ask the question: At what time have subjects attended enough to do better than always choosing default option? In the "33%, 33%, 33%" treatment, the fraction of rounds in which the best option is chosen is significantly higher than the fraction of rounds the default is best after just 9 seconds (at a significance level of 5%).[20] Thus, we will label a subject as having been "inattentive" in a round if 8 seconds or less was taken to make their decision. The vertical red line on Figure 7 indicates where the threshold for inattentiveness intersects with the cumulative density function, showing that in 39% of rounds subjects are revealed to be inattentive. The results that follow are robust to changes the threshold time (any time from 5 to 11 seconds).

6.2 Inattentiveness and Performance

Choice behavior is substantially different in those rounds in which subjects are revealed to be inattentive. Table 2 shows that when subjects are inattentive, the default effect is very strong: the default option is chosen far more often than it is best. Also, as the informativeness of the default increases, the default effect becomes even stronger. When subjects expect the default to be best 50% of the time, nearly all inattentive subjects select the default option. On the other hand, when subjects are attentive, they choose the default option in a proportion similar to the rate at which it is best.

Table 2. % rounds default chosen

Treatment	Inattentive	Attentive
33%, 33%, 33%	55%	37%
40%, 30%, 30%	83%	45%
50%, 25%, 25%	95%	51%
Overall	80%	43%

Given that inattentive subjects overwhelmingly choose the default option when there is an informative default, it is not surprising that they find the best option about as often as the default option is best. As a result, informative defaults improve the choice quality of inattentive decisions,

[20] For the other treatments, the threshold is higher, but we chose the more conservative approach of using the lowest threshold.

significantly so between the most informative default and the other defaults (p-values of 0.033 and 0.0524 using a two-sided t-test).[21]

Table 3. % round best chosen (inattentive rounds)

Treatment	Inattentive
33%, 33%, 33%	37%
40%, 30%, 30%	39%
50%, 25%, 25%	47%
Overall	42%

6.3 Attentiveness and Performance

As Table 4 indicates, attentive subjects do not always choose the best option. Instead, they find the best option in roughly two out of three rounds. We find that better defaults improve choice quality on aggregate for attentive decisions, albeit insignificantly so. The difference is not significant between any two treatments, either overall or between any two blocks of rounds (two-sided t-test, 10% significance level).[22]

Table 4. Percent of rounds best option chosen (attentive rounds)

	Rounds			
Treatment	1-12	13-24	25-36	Overall
33%, 33%, 33%	66%	56%	65%	63%
40%, 30%, 30%	69%	63%	63%	65%
50%, 25%, 25%	67%	65%	70%	67%
Overall	67%	62%	66%	65%

6.4 Drop Outs

The Drop Out Hypothesis predicts that there is one factor that might offset the improvements in choice quality for inattentive and attentive decisions, which is a possible increase in drop out behavior. Table 5 confirms this prediction by showing that the percentage of inattentive rounds increases as the default becomes more informative. When the default is no more likely than any

[21] Probit regressions run with clustering at the subject level produce p-values of 0.016 and 0.057.

[22] Regressions run with clustering at the subject level produce the same results.

other option to be best, subjects are inattentive in only 31% of rounds. On the other extreme, when the default is 50% likely to be the best option, subjects are inattentive in nearly half of the rounds. These differences are significantly different at the 1% level using a two-sided t-test.

Table 5. Percentage of inattentive rounds

Treatment	Overall
33%, 33%, 33%	31%
40%, 30%, 30%	38%
50%, 25%, 25%	49%
Overall	39%

6.5 AVF: "33%, 33%, 33%" Treatment

Having confirmed the Drop Out Hypothesis, we now turn to our underlying model. Using decision time as a proxy for the intensive margin of attention, we find some evidence of a suitable common (across subject) AVF in the "33%, 33%, 33%" treatment. While it would be preferable to estimate the AVF separately for each individual, we do not have enough choices in the "33%, 33%, 33%" treatment to do so.

Figure 8 shows average decision quality for each octile (8th) of decision times, with all "inattentive" octiles pooled together, and the quadratic fit to these data points, along with the 95% confidence intervals. While far from conclusive, this figure is broadly suggestive of the theory: the value function appears to be increasing and returns appear bounded. Given this AVF, it would be straightforward to back out the corresponding distribution of marginal costs of attention.

A fit to the logistic function, as in the example, produces a similar curve to this quadratic fit. The apparent absence of the convex portion in this graph makes sense because the environment is simple enough that any convex region should be relatively brief and may fall almost entirely in the first octiles.

6.6 AVF: Across Treatments

If we produce a quadratic fit for each treatment, then we once again find evidence consistent with our model. Figure 9 shows that the quadratic fit for the "50%, 25%, 25%" treatment falls above

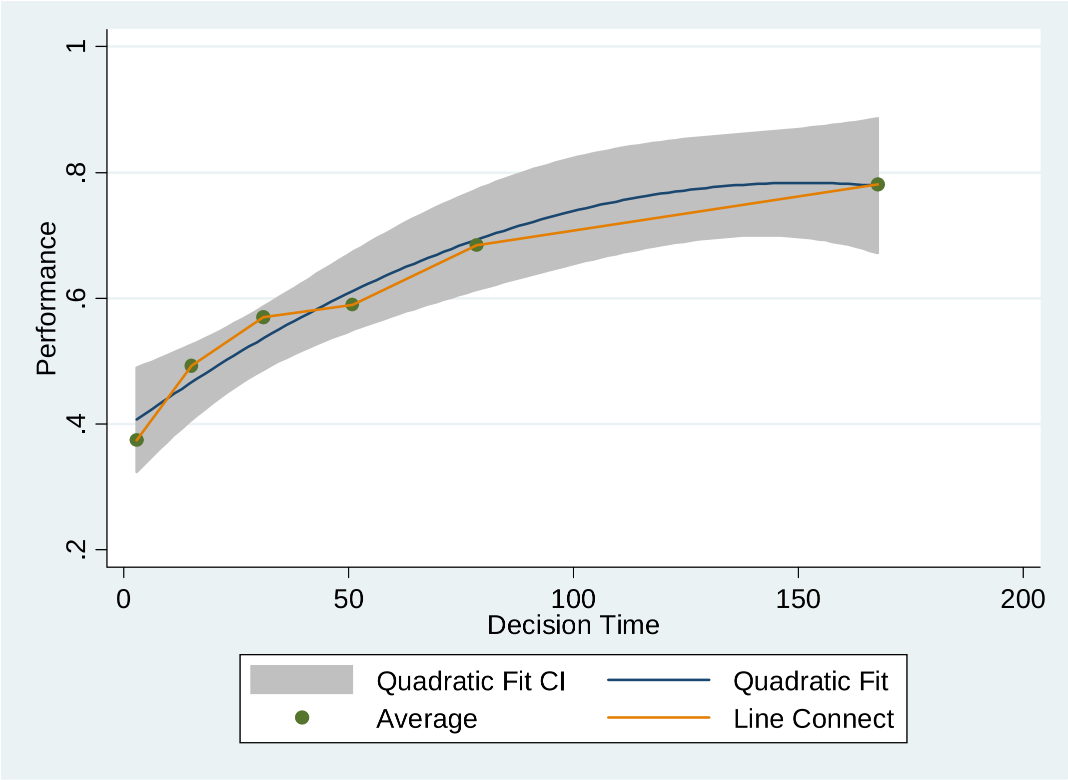

Figure 8: Average performance by decision time (33%, 33%, 33% treatment)

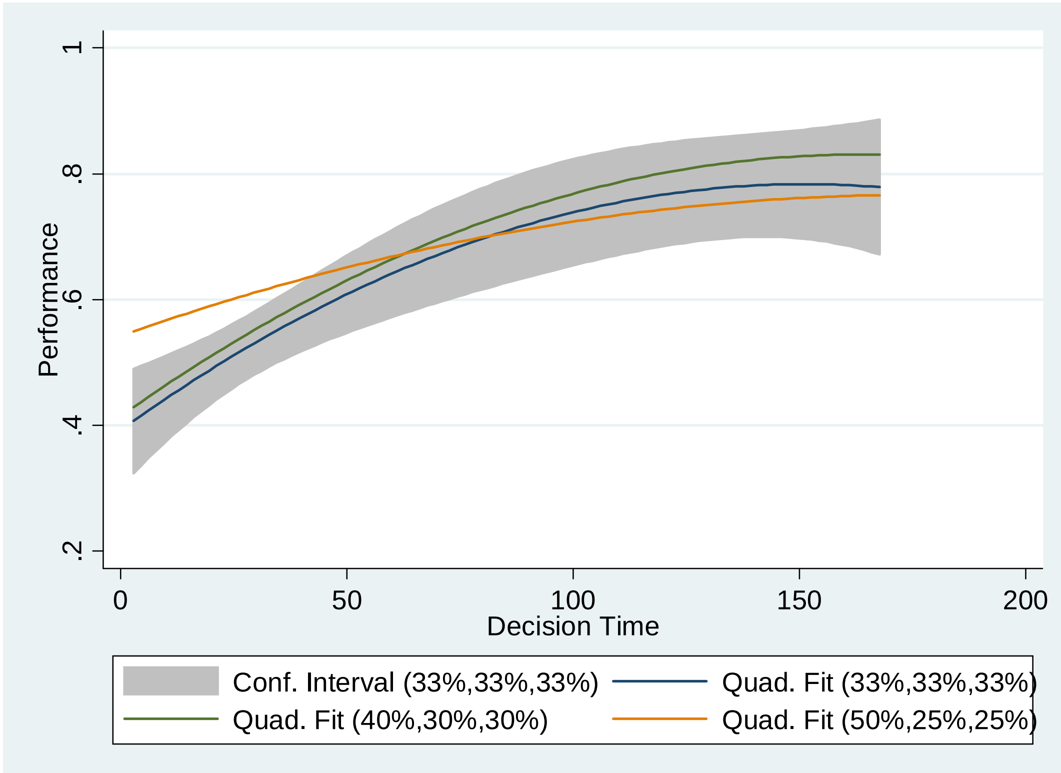

Figure 9: Average performance by decision time (across treatments)

the 95% confidence interval for the quadratic fit for the "33%, 33%, 33%" treatment for shorter decision times.

7 Active Choice

An alternative to the default policies described above is to have no default option at all, as suggested by Carroll, Choi, Laibson, Madrian, and Metrick [2009]. Because this active choice policy provides decision makers with the same information as the random default, our model suggests that it should produce the same number of inattentive subjects and the same overall choice quality.

To test this hypothesis, we ran another experiment, which was identical to the first, except that active choice was required – as no option was preselected. We call the previous experiment the "default" experiment and this new one the "active choice" experiment. In the active choice experiment, we observed a total of 42 students complete 1512 rounds (504 rounds per treatment) over 3 sessions. While all three treatments were run in this experiment, we only look at responses in the "33%, 33%, 33%" treatment because an active choice policy would not provide any information about the location of the best prize.

Table 6. Comparisons between experiments

	First Option Chosen		Percentage Inattentive Rounds		Best Option Chosen	
Treatment	Default	Active Choice	Default	Active Choice	Default	Active Choice
33%, 33%, 33%	43%	38%	31%	24%	55%	58%
40%, 30%, 30%	59%		38%		55%	
50%, 25%, 25%	72%		49%		58%	

As Table 6 shows, nearly a quarter of all subjects are deemed inattentive in the "33%, 33%, 33%" treatment of the active choice experiment. However, this is lower than in any treatment of the default experiment (two-sided t-test, 5% significance level). Our model is silent on why the amount of inattentiveness would drop, suggesting a positive behavioral effect of this policy.

8 Concluding Remarks

In this paper, we develop a model of attentional choice and formulate the Drop Out Hypothesis, which posits that an informative default will increase the number of attentional drop outs. We find evidence of this in a simple laboratory experiment, suggesting that a key challenge for default setters is how to best measure such drop out behavior in the field.

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10 Online Appendix: Complete Instructions

Welcome

You are about to participate in an experimental session designed to study decision making. You will be paid for your participation with cash vouchers at the end of the session.

Please silence your cellular phones now.

The entire session will take place through your computer terminal. Please do not talk or in any way communicate with other participants during the session.

We will start with a brief instruction period. During this instruction period, you will be given a description of the main features of the session and will be shown how to use the program. If you have any questions during this period, raise your hand.

When you have finished the experiment, remain quietly seated until your payment form has been prepared. This will take several minutes, so please wait patiently. Do not disturb those who are still working - you can read or do something equally quiet. This is important because participants will finish the experiment at different times.

Also, please raise your hand if you experience any unusual behavior from the computer program. We will occasionally walk through the room to make sure everything is running properly.

The experiment consists of 36 rounds, which are divided into 3 blocks of 12 rounds. There will be additional instructions before each block.

In each round, you will be shown 3 options, each of which contains 20 numbers. Each of the twenty numbers is a random integer between plus eighteen and minus eighteen (all equally likely), and each number is determined independent of the other numbers.

The value of each option is the sum of all 20 numbers. Your task will be to choose the option that has the highest value. You cannot use a calculator or scratch paper.

At the end of the experiment, we will randomly select three rounds for payment (one round from each of the 3 blocks). In **each** of the three rounds selected for payment, if you chose the option with the highest value, you will get $8, if not, you will get $4. Therefore, the maximum total payment is $24, and the minimum total payment is $12.

When a round starts, the first option will be selected, and if you make no changes before clicking the 'Finished' button, it will be recorded as your choice. You can change which option is selected by clicking on the button to the left of the option you want or by clicking anywhere on the option itself. You are free to change which option is selected at any time and as many times as you like.

Whenever you click on the 'Finished' button, the round will come to an end, and the selected option will be recorded as your choice. After a brief pause, you will be given the opportunity to either review the instructions again on the computer screen or proceed to the next round. This will continue until you have completed all 3 blocks, for a total of 36 rounds.

Next