Defaults and Attention: The Drop Out Effect

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Policy makers may try to reduce decision making errors by making a high quality option the default option. The positive effect of this policy can be undermined by "drop out" behavior in which the default is accepted hastily and with little regard for personal suitability. We measure the drop out effect in an experimental setting using response time as a proxy for attention. We find that this effect can completely offset the benefits of a high quality default. We use a model of costly attention to indicate conditions under which this drop out effect is rational and find moderate evidence that these conditions are satisfied.

ATTENTION ET OPTION PAR DÉFAUT : L'EFFET D'ABANDON

Les responsables de politiques publiques peuvent être tentés de réduire les erreurs de décision en établissant des options par défaut de bonne qualité. Les bénéfices attendus d'une telle politique peuvent cependant être menacés par un « comportement d'abandon », lorsque l'option par défaut est acceptée hâtivement avec peu de considération pour la compatibilité individuelle. Cet effet peut totalement annuler les bénéfices associés à une option par défaut de qualité. On utilise un modèle d'attention coûteuse pour indiquer les conditions dans lesquelles cet effet d'abandon est rationnel, et on trouve que ces conditions sont parfois respectées.

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INTRODUCTION

When choice options are complex, consumers may be confused and thus make mistakes. Even a simplified presentation of the available Medicare plans in the US requires decision makers to process a significant amount of information. For those seeking to understand the options and make a suitable choice, "spending an hour or two is not going to get the job done" (Thaler and Sunstein [2008], 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 (for instance, see Carroll et al. [2009]).

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 [2003], 186). Just such a policy was implemented for Medicare choice in Maine, where in an effort to identify an appropriate default, "ten plans meeting state coverage benchmarks were evaluated according to three months of historical data on prescription use" (Thaler and Sunstein [2008], 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.

Carroll et al. [2009] suggest that making a high quality option the default could have an unintended consequence: individuals may decide not to switch to a more suitable option because the costs of doing so are no longer worth incurring, which we call the "drop out" effect. Carroll et al. [2009] model the costs that generate the drop out effect quite generally, but mention that one possible source is the cognitive cost of evaluating options.[1]

Using the laboratory experiments of Caplin and Martin [2015], we provide evidence that the drop out effect can occur when evaluating options entails a cognitive cost. One of the advantages of using the lab to study the drop out effect is that we can offer an objectively best option, which allows us to precisely measure the impact of this effect. From this, we show that the drop out effect can completely offset the benefits of a high quality default.

We model the cognitive cost of evaluating options using a simple model of costly attention. For this model, we indicate conditions under which the drop out effect is rational. In our model, agents choose a level of attentional effort that balances the marginal cost and benefits of additional effort, and the benefits of additional attentional effort come in the form of improved decision making. Such a model is in the spirit of a growing literature around rational inattention theory (Sims [2003]), where agents choose information structures that balance the costs of more informative structures with the benefits, which also come in the form of improved decision quality.

1. Choi, Laibson and Madrian [2006] find evidence of the importance of cognitive costs when they use a "Quick Enrollment" intervention to study the impact of opt-out costs.

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We find moderate evidence that the conditions we identify are plausible by examining response time and decision quality in the experiments of Caplin and Martin [2015]. The time taken to reach a decision is regularly studied in psychology, yet response times have been little studied in economics. Exceptions include Wilcox [1993], Rubinstein [2007], Caplin, Dean and Martin [2011], Geng [2016], and Jin, Luca and Martin [2016].

The second section of this paper presents a model of costly attention and drop out behavior, and the third section provides experimental evidence on the drop out effect.

ATTENTIONAL CHOICE AND DROP OUT BEHAVIOR

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 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.

Costly Attention and Drop Out Behavior

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 and are given by $\mathrm{K}(\alpha) = k\alpha$. The parameter $k > 0$ is the marginal utility cost of attentional effort. This parameter could vary both across individuals and across time, yet is assumed known to each DM when the level of attentional effort is chosen.[2]

To determine the optimal level of attention, the DM weighs the costs of attentional effort, given by $\mathrm{K}(\alpha)$, against the quality of decisions for that level of attentional effort, given by the "attentional value function" $\mathrm{V}(\alpha)$. This attentional value function (AVF) measures decision quality in terms of expected utility.

To motivate the AVF, imagine 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. On the other hand, if the DM expends

2. While this assumption is standard in the rational inattention literature, it is admittedly a demanding one.

no attentional effort, and as a result receives no informative signals, then they can only expect the utility that arises from choosing in line with prior beliefs. An example of this form is provided in the Online Appendix, DOI: 10.3917/reco.pr3.0094.

To capture the relationship between the marginal cost of attention and choice quality at the optimal attentional level, we use the function $\alpha^*(k)$ where $\alpha^*(k) \in \arg\max_{a \geq 0}\{V(\alpha) - k\alpha\}$. The expected utility given by the AVF at this optimal level of attention indicates average choice quality for a specific marginal cost of attention. This relationship is illustrated graphically in the Online Appendix.

For some attentional value functions, there exists a critical cost level $\bar{k}$ at which it is optimal to drop out altogether and to choose zero attentional effort if and only if costs are above this threshold. We show generally when such a threshold exists and also when the cutoff threshold falls when there is a high quality default.

A Drop Out Cost Lemma

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 figure. In even simpler environments, the AVF may be entirely concave, with the most rapid learning taking place at the lowest levels of attentional effort. However, there are general properties for the AVF shape under which the drop out cost $\bar{k}$ is well behaved.

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

1. *Weak Monotonicity:* $\alpha_1 > \alpha_2 \Rightarrow V(\alpha_1) \geq V(\alpha_2)$.[3]
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* $\delta > 0$,

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

If the AVF satisfies these conditions, 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* $V : \mathbb{R}_+ \to [0,1]$ *satisfying Condition 1, there exists* $\bar{k}$ *such that* $\alpha = 0$ *is an optimal choice if and only if* $k \geq \bar{k}$.

3. One behavioral model that could generate a decreasing AVF is poor decision making in the face of higher cognitive load. Imagine DMs who can reduce uncertainty by expending attentional effort to obtain informative signals, but who choose poorly if they receive too many signals because processing signals impairs other aspects of decision making.

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.

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.

Drop Out Effect Conditions

We establish that under broad conditions high quality defaults incentivize additional drop out behavior.

> Proposition 1. *For* V^H *and* V^R *that satisfy Condition 1, if*
>
> *1)* $V^H(0) > V^R(0)$ *and*
>
> *2)* $V^H(\alpha) - V^R(\alpha) \in \left[0, V^H(0) - V^R(0)\right]$ *for all* $\alpha > 0$,
>
> *then the drop out cost is at least as high with the random default as with the high quality default, so that* $\bar{k}^H \leq \bar{k}^R$.

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^H and V^R.

The first condition requires that with no attention whatever, the high quality 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 random 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 a high quality 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 positive. The second part asserts that the increase in expected prize utility can never be higher than when there is no attention. This makes sense if the impact of the prior reduces with attentional effort.

There are three distinct attentional cost regions in terms of decision quality. For high levels of cost, $k > \bar{k}^{\mathrm{R}}$, 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, $k < \bar{k}^{\mathrm{H}}$, there is attentional effort with both the high quality and the random default, and once again higher decision quality. The most interesting region is where there is positive attention only with the random default,

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

On balance, which default produces higher choice quality depends on the distribution of attentional costs.

EXPERIMENTAL EVIDENCE

To study the drop out effect and to examine the plausibility of these conditions, we use the experiments of Caplin and Martin [2015], in which the subject has to identify which of three options has the highest numeric value and the value of each option is hard to assess since it is expressed in words as the sum of twenty integers.[4] In these experiments, the first option is always the default option, and subjects are informed of the probability that the default is best.[5] We interpret knowledge of these probabilities as the end process of either direct knowledge of the rule used to select a default or experience with the default, which allows us to study defaults in an individual decision making context.[6] Subjects face three treatments in each session, each of which lasts for a block of 12 rounds. In each session, there is a different probability that the default is best: 33%, 40%, or 50%. The order of the treatments is randomized between subjects.

The Drop Out Effect

To reveal the drop out effect, we rely on response time data from the 53 experimental subjects studied by Caplin and Martin [2015]. Across treatments, subjects took a median of 22 seconds to reach a decision. The mean response time

4. A similar task is used in the experiments of Caplin, Dean and Martin [2011], Caplin and Martin [2011], Martin [2015] and Jin, Luca and Martin [2016].

5. Haan and Linde [2016] also study defaults when options involve mathematical operations, but do not inform subjects of the underlying probabilities.

6. Altmann, Falk and Grunewald [2013] study default selection in the sender-receiver framework and show that default effects can depend on the alignment between sender and receiver preferences.

was 43.4 seconds, and the standard deviation was 58.0 seconds. Subjects faced no time limit, and the maximum time taken for a decision was 562 seconds. We follow Caplin and Martin [2015] in calling decisions that take 8 seconds or less "inattentive" decisions, though the results that follow are robust to moving this boundary anywhere from 5 seconds to 11 seconds.

These attentional drop outs are quite different from more considered decisions. For instance, drop outs are much more likely to choose the default option. In the 33% treatment, 55.4% of inattentive decisions involved choosing the default as compared to 37.0% of considered decisions. In the 40% treatment, 82.6% of inattentive decisions involved choosing the default as compared to 44.9% of considered decisions. In the 50% treatment, 94.5% of inattentive decisions involved choosing the default as compared to just 50.6% of considered decisions.

We also observe additional drop outs when the default is of higher quality. In the 33% treatment, 30.7% of subjects are inattentive; in the 40% treatment, 38.1% of subjects are inattentive; and in the 50% treatment, 48.7% of subjects are inattentive.

Because there is an objectively best answer in each round, we can measure decision quality with the percentage of rounds in which the best option was chosen. We find that for this experiment the drop off effect completely offsets the value of providing higher quality defaults. The percentage of rounds the best option is chosen is 55.3% in the 33% treatment, 55.2% in the 40% treatment, and 57.5% in the 50% treatment.

Experimental Evidence of Condition 1

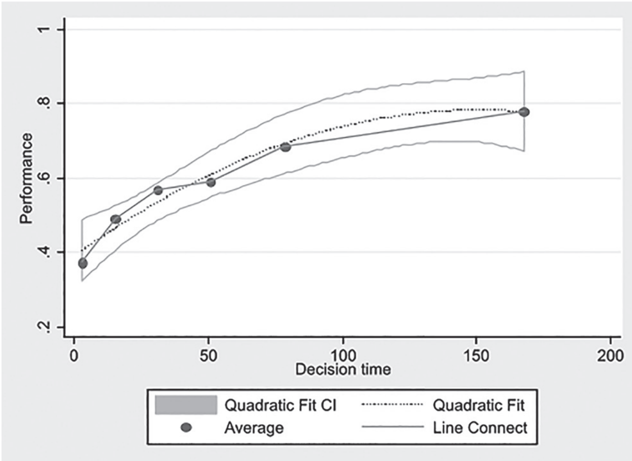
Using response time as a proxy for the intensive margin of attention, we find some evidence of a suitable common (across subject) AVF in the 33% treatment. While it would be preferable to estimate the AVF separately for each individual, we do not have enough choices in the 33% treatment to do so. Given an AVF, it would be straightforward to back out the corresponding distribution of marginal costs of attention.

Figure 1 shows average decision quality for each octile (8th) of response 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. One potential issue is endogeneity: such a relationship would appear if higher ability subjects took longer to make a decision.[7]

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. However, note that the AVF appears to satisfy both monotonicity and bounded returns.

7. One way to account for this heterogeneity in the theoretical model would be to have separate parameters for attentional effort and ability.

Figure 1. *Average performance by response time (33% treatment)*



Experimental Evidence of the Drop Out Effect Conditions

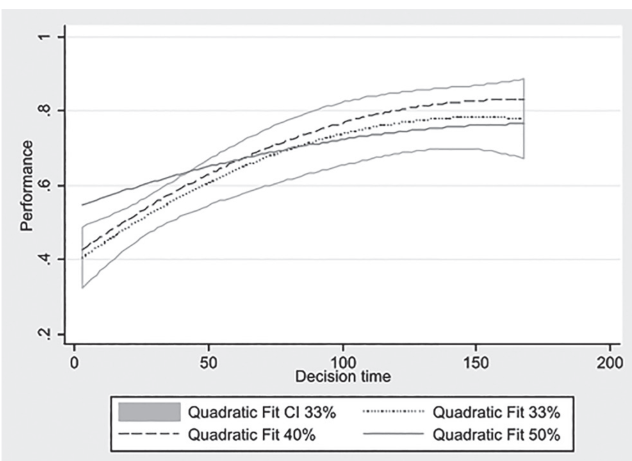
We produce a quadratic fit for each treatment and find mixed evidence of the required conditions. Figure 2 shows that the condition $V^H(0) > V^R(0)$ is satisfied for all treatments, but significantly so only for the 50% treatment.

On the other hand, the condition that

$$V^H(\alpha) - V^R(\alpha) \in \left[0, V^H(0) - V^R(0)\right] \text{ all } \alpha > 0,$$

does not appear to be satisfied, as the AVF for the 50% treatment appears to dip below the others. However, these differences are not significant.

Figure 2. *Average performance by response time (across treatments)*



CONCLUDING REMARKS

In this paper, we find evidence of the drop out effect in a simple laboratory experiment where the only costs for changing to a more suitable option are psychological attentional costs. This confirms the drop out effect is potentially important and suggests that attentional costs can generate it.

Methodologically, we see a large future role in experimental economics—both in the lab and in the field—for decision times, response times, and consideration times. In addition to the time taken to reach a decision, it is possible to collect richer data related to time and choice. For instance, Caplin, Dean and Martin [2011] elicit how choices evolve as an individual considers a choice set for more time, called "choice process data."

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