# Benefits of Neuroeconomic Modeling:
# New Policy Interventions and Predictors of Preference

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Neuroeconomics aims at providing a detailed computational and neurobiological account of the decision-making process that will serve as a foundation for a better understanding of human behavior and well-being (Fehr and Rangel 2011). This means that data such as neural activity, response times (RT), and eye movements play an important role in this research program. However, much opposition to neuroeconomics has centered on the idea that standard economic theory makes no predictions about non-choice data. This stems from a long-held reluctance among economists to model the *process* of decision-making and to instead focus only on its *outcome*, namely the resulting choice. To address this, recent neuroeconomic models have sought to demonstrate the usefulness of jointly relating choice frequencies and process measures to underlying latent valuations. Here we show, in particular, that (i) neuroeconomic drift-diffusion models (DDMs) yield new – empirically validated – insights into the potential suboptimalities of *individual* decision-making that can be mitigated with novel policy interventions, and (ii) that the time it takes to make decisions provides an informative signal about people's preferences. Thus, additional measures related to the choice process can be useful for both positive and normative economics. Overall, we use the DDM to make a general point that there is substantial value to jointly modeling choices and other process measures, even if a researcher is only concerned with choices.

The problem that the DDM addresses is that of stochastic choice. Inconsistent choice behavior is well documented and necessitates the use of probabilistic approaches such as logistic choice models (Luce 1959), random utility theory (McFadden 1973), and Quantal Response Equilibria (McKelvey and Palfrey 1995). Some have argued that such probabilistic behavior is still utility-maximizing behavior and that it only appears noisy due to unobserved characteristics of the alternatives or the decision maker (McFadden 1973). Others have instead argued that it is the result of a Bayesian-like process (such as a DDM), where individuals must compare noisy internal representations of the attractiveness of the options (Busemeyer 1985), which may lead to choice mistakes. On the basis of choice data alone it is not possible to distinguish between these two explanations, but unlike random utility theory, the DDM correctly predicts additional observables such as RTs, which would seem to give it a distinct advantage in the debate.

Here we discuss some positive and normative implications of the DDM. First, we briefly introduce the DDM, which will be the theoretical basis for our empirical applications. Second, we show that subjects misallocate their time and miss out on high-stakes choices by getting stuck on low-stakes ones. To prove this point, we introduce a simple intervention that improves their performance. Third, we show that with the DDM approach it is possible to predict subjects' indifference points using only their RTs.

## I. Drift-Diffusion Model of Choice

While the DDM and other related models are relatively unknown in economics, they have been widely used in perception research, where the decision maker must observe explicitly stochastic evidence (e.g. a screen full of flickering dots) and make an objective judgment about the state of the world (e.g. some of the dots are moving to the left or right). It has been shown countless times that the DDM is able to capture accuracy rates and RT distributions in these tasks.

In economics, choice options are usually not explicitly stochastic in nature. However, stochasticity arises when assessing the decision utility of the choice options, due to noise in how our brains represent them. When deciding between two possible choice options $X$ and $Y$, the decision maker observes value signals $x_t$ and $y_t$ randomly drawn from two distributions with means $u_x$ and $u_y$ respectively. One can think of $u_x$ and $u_y$ as the "true" underlying values of the choice options. After observing a pair of signals at time $t$, the decision maker updates his relative decision value (RDV), which we denote $V_t$. One can think of $V_t$ as akin to a Bayesian posterior that option $X$ is preferred to option $Y$. The temporal evolution of the RDV can be written as

(1) $$V_t = V_{t-1} + d(x_t - y_t)$$

where $d$ is a parameter that governs the drift rate at which the RDV evolves.

Assuming that the signals are being drawn from Normal distributions, we can rewrite the model as

(2) $V_t = V_{t-1} + d(u_x - u_y) + \varepsilon_t$

with $\varepsilon \sim N(0, \sigma^2)$, where σ is a second parameter governing the noise in the process.

The sampling process continues until the RDV reaches a pre-defined choice threshold of $\pm a$. A value of $+a$ indicates a choice for option *X*, while a value of $-a$ indicates a choice for option *Y*. One can think of the choice threshold as a pre-defined confidence level that the decision maker requires before committing to his choice. Notice that because the RDV lacks units, we are free to let either *d*, $a$, or σ be equal to 1. What is important to note is that these parameters are assumed to be set by the decision maker beforehand (or are a property of the neural decision circuitry) and thus do not change across trials, though they may vary across conditions or experiments.

One can see from the model that the time it takes to make a decision depends critically on $|u_x - u_y|$. When this difference is large, the RDV evolves with a steep expected slope and decisions are made quickly, whereas when the difference is small, the RDV evolves with a shallow expected slope and decisions are slow (Fig. 1). At indifference, choices are driven purely by noise.

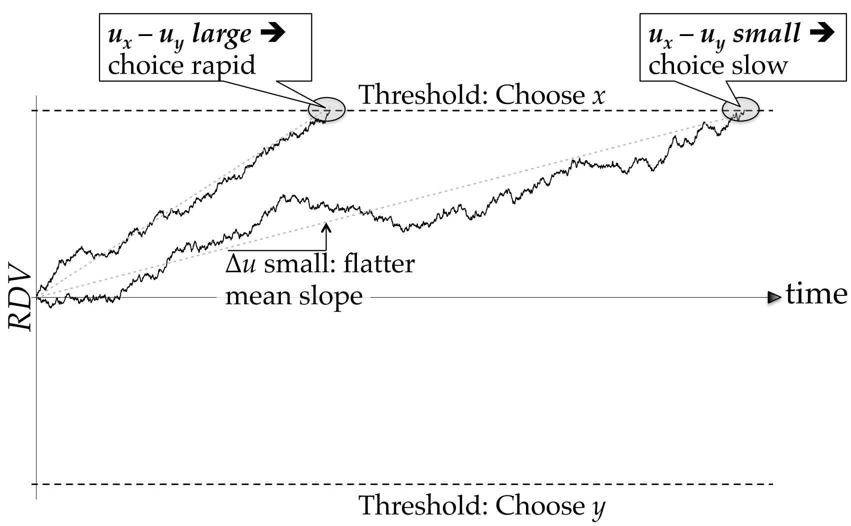


FIGURE 1. THE DRIFT-DIFFUSION MODEL

This model is appealing both theoretically and empirically. The DDM is known to implement the sequential probability ratio test, which in environments where $|u_x - u_y|$ is fixed, is the optimal decision rule in the sense that for a desired accuracy rate, it minimizes the expected time to reach a decision (Wald and Wolfowitz 1948). Empirically, although this assumption is often violated, the model has been very successful at capturing a wide variety of decisions. Furthermore, the threshold-based decision rule in the model mimics the way the brain actually works. Neurons (including the ones that encode decision values and cause decisions) transmit information using all-or-nothing signals known as "action potentials", which only occur once the inputs to the neurons reach a critical threshold of activity. The strength of evidence is thus encoded in the frequency of action potentials, known as the "firing rate."

For economic decisions, Krajbich, Rangel and colleagues have shown that the DDM, and the extended multi-option version, accurately capture choice probabilities and RTs of subjects making binary and trinary food choices (Fig. 2), consumer purchasing decisions, and temporal discounting decisions (Krajbich, Armel and Rangel 2010; Krajbich and Rangel 2011; Krajbich et al. 2012). In several of these studies visual attention was also incorporated into the DDM and it was shown that there is a reliable correspondence between gaze time and choices. More specifically, options that receive more attention also receive more evidence in their favor and so eye-tracking data can be used to improve choice predictions.

In a more recent paper (Krajbich et al. 2014), we demonstrated that the model could predict new subjects' behavior in three different social-preference tasks *without any parameter fitting*, i.e. using previously-estimated parameters from the food-choice experiments (Fig. 2).

Taken together, these results provide strong evidence that the DDM is capturing a general choice process for economic decisions. The DDM thus holds great promise as a way to unify the currently divergent approaches to modeling preferences over risk, time, social allocations, etc. Furthermore, as we will discuss in the next two sections, its ability to predict behavior across tasks, subjects and environments is just one benefit of the DDM.

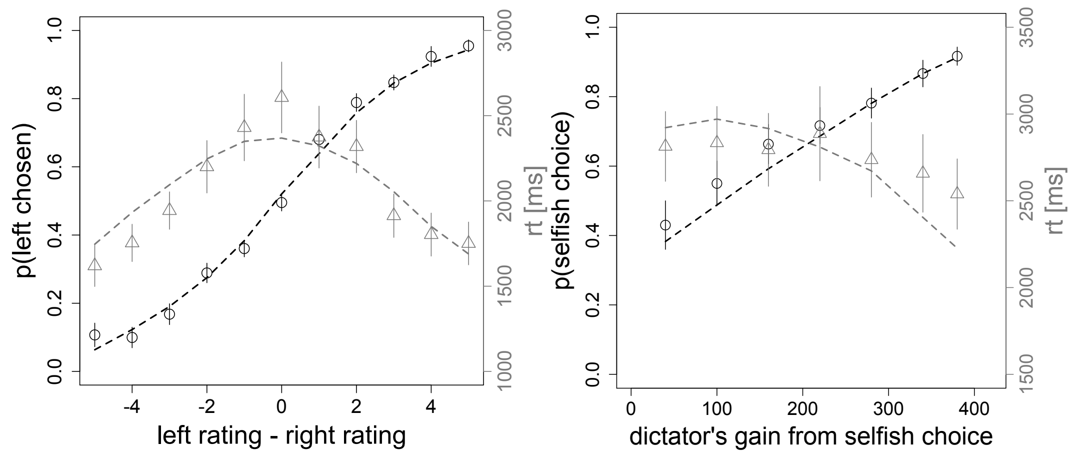


FIGURE 2. SIMULTANEOUS CHOICE AND RESPONSE TIME (RT) PREDICTIONS OF A DDM WITH THE SAME PARAMETERS IN BINARY FOOD CHOICE (LEFT) AND DICTATOR-GAME EXPERIMENTS (RIGHT).

*Note:* Choice probabilities and RTs are plotted on the left and right vertical axes, respectively, with choice probabilities in black circles and RTs in gray triangles. Data are presented as points with standard error bars across subjects, while DDM predictions are presented as dashed lines.

## II. The Opportunity Cost of Time

One important finding from the DDM approach is that decision makers spend more time on choices where $|u_x - u_y|$ is small, compared to large. This is economically counterintuitive if time is a sufficiently valuable resource. If a decision maker is nearly indifferent between two choice options then she should just flip a coin and use her valuable time for other purposes.

The DDM explanation for this phenomenon is that people do not know $|u_x - u_y|$ and so do not realize how close they are to indifference. A common assumption in these models is that decision-makers do not know the value of the RDV, only whether it has reached a threshold or not. This is analogous to how neurons will fire only once a threshold of activity is reached. Otherwise there is no way to know how close to threshold the neuron is. Similarly, the decision-maker does not know whether she is on the verge of reaching a decision, or no closer than when she started (Ratcliff 2006).

To study the suboptimal use of time implied by the DDM, we devised an experiment where the opportunity cost of time was under our control (Oud et al. 2014). In the experiment, subjects made 100 incentivized binary choices between different snack foods for which we had previously measured their willingness-to-pay (WTP). We constructed 50 “high stakes” and 50 “low stakes” trials with large and small differences in WTP, which were shown in a pseudorandom sequence. Subjects only had 150 seconds total (with 1.25 second pauses between trials) and no subject was able to complete all 100 choices. Subjects knew that any unreached choices would be made randomly.

Given the clear opportunity cost of time, optimal decision-makers should quickly decide on the low-stakes trials to ensure they reach more of the high-stakes ones. Instead we see the opposite. Subjects took an average of 1.65 s on the low-stakes trials, while taking only 1.11 s on the high-stakes ones. This came at a substantial cost to the subjects, as they missed out on an average of 44 trials, equal to an average of $20.10 left on the table per subject if all the trials had been paid out.

To further demonstrate sub-optimality, in a follow-up task with the same subjects, we attempted to improve their welfare, as measured by choice surplus (defined as the mean-subtracted difference in WTP between the chosen option and the worst option on the screen), by creating an intervention where they were prompted to "Choose Now" if they spent too long on a choice. If they did not make a choice within half a second of seeing that message, the choice was randomly made for them, and the experiment continued with a new choice pair. Since RT increases with proximity to indifference, the intervention should primarily cut off the low-stakes trials, thus allowing subjects to reach more high-stakes trials. Critically, the intervention mechanism used only decision-time information and did not use any information about the WTPs for the items. Thus we only used information that was also available to the subjects.

We found that indeed this intervention substantially improved subjects' choice surplus in the experiment. Interestingly, the intervention also had some spillover effects. Subjects markedly improved in non-intervention blocks (alternated with intervention blocks), but only after experiencing the intervention (Fig. 3).

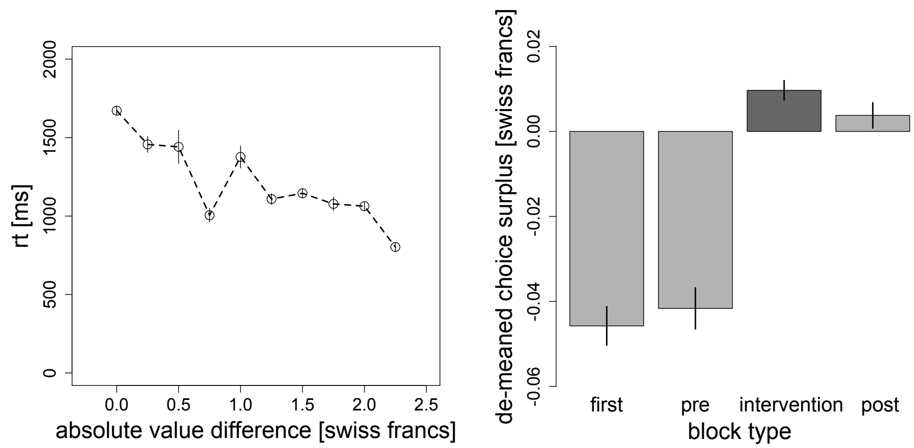


FIGURE 3. RESULTS FROM THE TIME-INTERVENTION STUDY, WITH MEAN RT AS A FUNCTION OF THE DIFFERENCE IN WTP BETWEEN THE TWO FOOD ITEMS (LEFT) AND INDIVIDUALLY DE-MEANED CHOICE SURPLUS IN THE DIFFERENT CHOICE BLOCKS (RIGHT).

*Note:* "First" denotes the first choice block (N=49), "pre" denotes non-intervention blocks preceding the first intervention block (N=29), "intervention" denotes the intervention blocks (N=49), and "post" denotes non-intervention blocks occurring after the first intervention block (N=49).

With this simple experiment we have shown that people are suboptimal on at least two levels. First, our results are consistent with the view that people must construct their preferences at the time of choice and that low-stakes choices take more time than high-stakes ones. Still, it was possible that people could be using an optimal decision rule, conditional on the neural constraints of the preference-construction process, by, for example, cutting off long decisions. We have shown that this is not the case, since our subjects sub-optimally allocated their valuable time and were unable or unwilling to cut themselves off when decisions took too long. Had they been responding optimally to the time-constraints, we should not have been able to improve their performance on the task, using no additional information. It is also informative that subjects' performance improved in post-intervention blocks that lacked the intervention, implying that the intervention helped subjects to adjust their behavior in a beneficial way. Overall, we see this experiment as a proof-of-concept that it may be possible to improve peoples' welfare with simple interventions or behavioral training.

## III. Using RTs to Predict Choices

Given that choices are probabilistic, it can often be time-consuming and difficult to establish an individual's preferences, since in most applications, we use only choice outcomes as the basis for inference. However, the DDM suggests that we should be able to do better by additionally utilizing RTs.

To investigate this possibility, we looked at an existing Ultimatum Game dataset from our laboratory (Baumgartner et al. 2011). In this experiment, each subject played sixteen rounds of the Ultimatum Game in the responder role. Each trial, the subject received an offer of \$4, \$6, \$8, or \$10 out of a possible \$20 from anonymous, randomly re-matched partners. The subject could either accept the offer, or reject it and leave both players with \$0. Consistent with the DDM, 89% (16 out of 18) of the subjects made probabilistic choices in the sense that the same offer (from different anonymous partners) was both rejected and accepted in different trials.

In this experiment the DDM also predicts that the transition from accepting to rejecting offers will coincide with the longest RTs. To test this prediction, we examined how many subjects had their highest mean RT at the offer level closest to their indifference point (i.e. 50% acceptance rate). With only 3-5 choices per offer level, this basic DDM prediction was borne out in 16/18 of our subjects (Fig. 4).

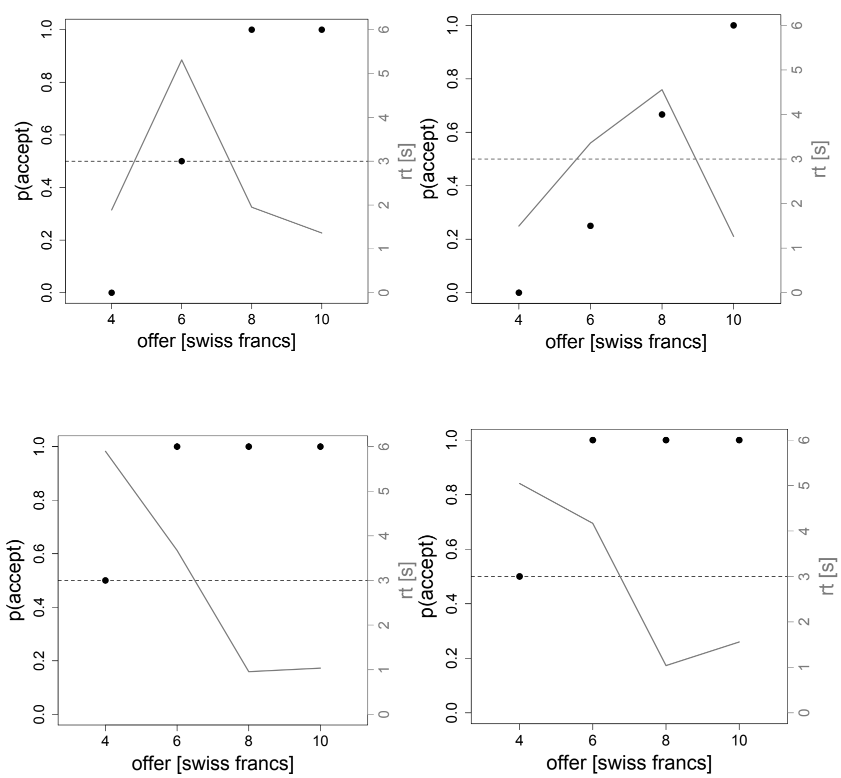


FIGURE 4. CHOICES AND RTS FOR FOUR SUBJECTS IN THE ULTIMATUM GAME, SHOWING THAT PEAK RTS COINCIDE WITH CHOICE FREQUENCIES THAT ARE CLOSEST TO INDIFFERENCE.

*Note:* Choice probabilities (black circles) and RTs (gray lines) are plotted on the left and right vertical axes, respectively. The dashed line indicates indifference between accepting and rejecting.

Figure 4 also demonstrates another use of the DDM. The bottom two subjects accepted every offer above \$4 and so if we had data for only those offer levels (such limitations often apply in small datasets) we would be unable to say whether these subjects gave any consideration to the fairness of the offers before accepting them. Yet looking at the RT curves there is clear evidence that these subjects found it more difficult to accept offers of \$6 compared to \$8, and so we would correctly conclude that these subjects did care about the fairness of the offers and extrapolate that they would reject low enough offers.

More generally, the DDM suggests that RTs can be used to measure the strength of preference (Clithero and Rangel 2014; Chabris et al. 2009). As an example, suppose we observe an individual express a preference for A over B in 2 seconds, and A over C in 1 second. Using standard revealed preference theory, we could not make a prediction about the preference relation between B and C. On the other hand, the DDM makes a very clear prediction. The fact that A over B was a slower decision than A over C directly implies that B is likely closer in value to A. Thus the DDM predicts that B will likely be chosen over C. In this way, the DDM can predict future decisions for which revealed-preference theory alone makes no prediction. This example illustrates how analyzing RTs can enable researchers to more efficiently estimate preferences from a limited number of observed choices.

## IV. Conclusions

We conclude by noting that neuroeconomic models such as the DDM provide strong ties between traditional choice behavior and non-choice measures such as RT, attention, and brain activity. Here we have demonstrated how one such measure, RT, can be used to inform both positive and normative economics. Importantly, RTs can often be collected at no cost and so it is wasteful to not make use of them.

Of course, more research is necessary to investigate the boundaries of where these models can be usefully employed. For example, predictions of the DDM are likely to be less accurate in strategic environments. In such settings it often requires time to determine how actions map into outcomes and/or identify optimal strategies (Rubinstein 2013). The DDM we've presented is not a model of puzzle solving or of explicit calculation, but rather a model that captures choices that depend only on ones' own subjective preferences.

We should also note that the model described here is a rather simple version of the DDM. This simplicity entails a cost, namely that this particular form of the DDM will not always be *the* best fitting model on any particular dataset. However, we have found that our formulation of the model provides a good balance between simplicity and accuracy and is thus a useful predictive tool.

We find it particularly promising and exciting that the DDM is able to incorporate attention to predict behavior across different choice environments. These results address important concerns about the ability of neuroeconomics to provide useful alternatives to existing models of economic behavior, and they give us hope that we may be able to replace the current array of behavioral models with a more unified approach towards decision making. This work thus invites new research into the scope of the model and what factors influence its key parameters.

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